NAIRU Estimation of 28 EU-member States

Master's Thesis Submitted to

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Abstract

The non-accelerating inflation rate of unemployment (NAIRU) is an unemployment rate or range of unemployment rates that produces a stable rate of inflation. NAIRU is usually difficult to estimate since it is a hidden variable. In this thesis, the author allows time-varying NAIRU, and uses a structual model with forward and backward looking Phillips curves to estimate the output gap and unemployment gap. The author finds that in general, the negative relations between unemployment gap and inflation rate are significant across EU-member states. This method of capturing the relationship between unemployment and inflation is better than that of King and Watson's, implied by the indicators of Pearson's correlations, and also because of the potential ability of using our method to predict near future inflation rate.

Keywords: Bayesian Inference, Forward-looking Phillips Curves, NAIRU, New-Keynesian Model

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Contents

List of Abbreviations

Corr.	**Corr**elation
CPI	**C**onsumer **P**rice **I**ndex
EU	**E**uropean **U**nion
HICP	**H**armonised **I**ndex of **C**onsumer **P**rices
MCMC	**M**arkov **C**hain **M**onte **C**arlo
MH	**M**etropolis-**H**asting
NAIRU	**N**on-**a**ccelerating **I**nflation **R**ate of **U**nemployment
Po.Sd	**Po**sterior **S**tan**d**ard Error
RWM	**R**andom **W**alk **M**etropolis

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1 Introduction

1.1 Relationship between Inflation and Unemployment

The *non-accelerating inflation rate of unemployment* (NAIRU) is an unemployment rate or range of unemployment rates that produces a stable rate of inflation: if the unemployment rate is lower than the NAIRU then the inflation rate will tend to rise, and *vice versa*. The concept arises from Friedman (1968), and numerous works (*e.g.*, Staiger et al. (1997)) linked the relationship between inflation and unemployment to the Phillips curve.

The negative relationship between inflation and unemployment is hard to detect in the raw data. According to King and Watson (1994), this negative relationship can only be found in the business-cycle frequency. To confirm this point, we filter the monthly time series of unemployment and inflation rate of the 28 EU-member states into 3 frequencies, namely, zero frequency, business-cycle frequency (18 to 60 months), and the rest, see Figure 1 – Figure 28 in the Appendix A. We then calculate the Pearson's correlation of the two monthly time series in business-cycle frequency for each country. The results are presented in Table 1. From the table we see that significant negative correlations exist in most of the EU-member states. However, there are a few "outliers," in which positive correlations are observed, some of which are even 1%-significant. These suggest potential flaws in the King and Watson's method of capturing the relationship between inflation and unemployment.

In this thesis we allow time-varying NAIRU with a stochastic time trend. The author tries to capture the inflation-unemployment relationship by the interaction between unemployment and the NAIRU. In the end the author confirms that inflation rate varies with the unemployment gap (*i.e.*, the difference between the real unemployment rate and the NAIRU, due to the normal regidities): the inflation rate goes up when the real unemployment rate falls below the NAIRU, and *vice versa*.

1.2 Literature Review

Various literatures studied the measurement of NAIRU. The ones that are related closely to this thesis are the literatures that studied the measurement of NAIRU through backward-looking Phillips curve. Some of those are Blanchard and Katz (1997), Gordon (1997), Apel and Jansson (1999), Laubach (2001). This thesis also utilizes the forward-looking New-Keynesian Phillips curve, which assumes monopolistic competitive market set-up and sticky price. This could be traced to Calvo (1983) and Rotemberg (1982).

Country	Corr.	Time Horizon	Country	Corr.	Time Horizon
Austria	-0.6062^{**}	Jan.1994 – Oct.2013	Belgium	0.0053	Jan.1983 – Oct.2013
Bulgaria	0.2027^{**}	Jan.2000 – Oct.2013	Crotia	-0.0222	Jan.2000 – Oct.2013
Cyprus	-0.5701^{**}	Jan.2000 – Oct.2013	Czech Rup.	-0.7312^{**}	Jan.1998 – Oct.2013
Denmark	0.1794^{**}	Apr.1986 – Oct.2013	Estonia	-0.4248^{**}	Feb.2000 – Sep.2013
Finland	-0.6301^{**}	Jan.1988 – Oct.2013	France	-0.8263^{**}	Jan.1983 – Oct.2013
Germany	-0.1908^{*}	Jan.1991 – Oct.2013	Greece	-0.7086^{**}	Apr.1998 – Oct.2013
Hungary	-0.3625^{**}	Jan.1996 – Sep.2013	Ireland	-0.5562^{**}	Jan.1983 – Oct.2013
Italy	-0.7639^{**}	Jan.1983 – Oct.2013	Latvia	-0.4086^{**}	Oct.2001 – Sep.2013
Lithuania	0.4354^{**}	Jan.1998 – Oct.2013	Luxembourg	-0.5437^{**}	Apr.1986 – Oct.2013
Malta	0.0148	Jan.2000 – Oct.2013	Netherlands	-0.1295^{*}	Apr.1986 – Oct.2013
Poland	-0.1287	Jan.1997 – Oct.2013	Portugal	-0.7838^{**}	Jan.1983 – Oct.2013
Romania	-0.3388^{**}	Jan.1997 – Oct.2013	Slovakia	-0.1775^{**}	Jan.1998 – Oct.2013
Slovenia	-0.6448^{**}	Jan.1996 – Oct.2013	Spain	-0.7472^{**}	Apr.1986 – Oct.2013
Sweden	-0.6819^{**}	Jan.1983 – Oct.2013	UK	-0.1208^{**}	Jan.1971 – Aug.2013

Table 1: Pearson's Correlations between Inflation and Unemployment in the Business-Cycle Frequency. * denotes 5%-significance; while ** denotes 1%-significance. The countries with positive correlations are marked in red.

This thesis is a follow-up project of Cui et al. (2014), in which they incorporated unemployment into standard New Keynesian model through linking output gap and unemployment gap implied by Okun's law, and developed a structual model with forward and backward looking Phillips curve. They then used the model to estimate the NAIRU of the US. In this thesis, the same model is utilized on EU-member states. All notations will be kept the same with their paper in order to facilitate comparisons.

2 The Model

2.1 The State Equations

The author uses the structural model by Cui et al. (2014): Denote the real GDP as Y_t, and the potential output (*i.e.*, the output in absence of price regidities) as Y_t^n, and define $y_t = \log Y_t$,

$y_t^n = \log Y_t^n$. Then the output gap y_t^g is defined through

$$y_t = y_t^n + y_t^g$$

Following Harvey (1985), Watson (1986) and Clark (1987), the log of the potential output, y_t^n, can be assumed to follow a random walk with drift:

$$y_t^n = \mu + y_{t-1}^n + \varepsilon_t^n \quad , \qquad \varepsilon_t^n \sim \mathcal{N}\left(0, \sigma_n^2\right)$$

and the output gap, y_t^g, can be assumed to be an AR(2) process to allow for sluggishness:

$$y_t^g = \rho_1 y_{t-1}^g + \rho_2 y_{t-2}^g + \varepsilon_t^g \quad , \qquad \varepsilon_t^g \sim \mathcal{N}(0, \sigma_g^2) \tag{2.1}$$

Denote the inflation rate as Π_t, and its steady state as $\overline{\Pi}$. Moreover, we use π_t to denote the log-deviation of inflation rate from the steady state: $\pi_t := \log(\Pi_t) - \log(\overline{\Pi})$. Cui *et al.* provided the following New-Keynesian Philips Curve

$$\pi_t = \gamma_f \mathrm{E}_t\left(\pi_{t+1}\right) + \gamma_b \pi_{t-1} + \lambda\kappa y_t^g + \varepsilon_t^\pi \quad , \qquad \varepsilon_t^\pi \sim (0, \sigma_\pi^2)$$

where

$$\gamma_f = \frac{\beta}{1+\zeta\beta} \quad , \qquad \gamma_b = \frac{\zeta}{1+\zeta\beta} \quad , \quad \lambda = \frac{(1-\alpha)(1-\alpha\beta)}{\alpha(1+\zeta\beta)} \quad , \qquad \kappa = \sigma + \eta$$

in which $\beta \in (0,1)$ is the discount rate of future profits, $\alpha \in (0,1)$ is the probability that intermediate firms don't change price (*i.e.*, price regidities), ζ measures the elasticity of the indexation to past inflation [1], σ is the elasticity of consumers' intertemporal substitution between today's consumption goods and tomorrow's consumption goods, η is the disutility from labor market supply. Solving forward and they got

$$\pi_t = \theta_0 y_t^g + \theta_1 y_{t-1}^g + \theta_2 \pi_{t-1} + \varepsilon_t^\pi \tag{2.2}$$

where

$$\theta_0 = \frac{\lambda\kappa}{\gamma_0\left(1-\gamma_1\rho_1-\gamma_1^2\rho_2\right)} \quad , \qquad \theta_1 = \frac{\lambda\kappa(1-\gamma_1\rho_1)}{\gamma_0\left(1-\gamma_1\rho_1-\gamma_1^2\rho_2\right)} \quad , \qquad \theta_2 = \frac{\gamma_b}{\gamma_0}$$

[1] If the firm i cannot change price, the price P_{it} will be

$$P_{it} = P_{it-1}\overline{\Pi}^{1-\zeta}\Pi_{t-1}^{\zeta}$$

Therefore, based on this relationship, ζ measures the the elasticity of the indexation to past inflation.

with

$$\gamma_1 = \frac{1 - \sqrt{1 - 4\gamma_f \gamma_b}}{2\gamma_b} < 1 \ , \qquad \gamma_0 = \frac{1 + \sqrt{1 - 4\gamma_f \gamma_b}}{2}$$

One can refer to their paper for the details of the derivation.

2.2 The Measurement Equations

The equations (2.1) and (2.2) serve as the "state equations," in which y_t^g, u_t^g and π_t are unobservable. This requires us to find "measurement equations" to facilitate the use of Kalman filter.

First, let u_t denote the unemployment rate, and u_t^n denote the NAIRU. Then the unemployment gap u_t^g is defined through

$$u_t = u_t^n + u_t^g$$

The NAIRU process can be assumed to be a random walk following Basistha and Nelson (2007):

$$u_t^n = u_{t-1}^n + \varepsilon_t^u \ , \qquad \varepsilon_t^u \sim \mathcal{N}(0, \sigma_u^2)$$

Based on the two equations above, we have

$$u_t - u_{t-1} = \left(u_t^g - u_{t-1}^g\right) + \left(u_t^n - u_{t-1}^n\right) = u_t^g - u_{t-1}^g + \varepsilon_t^u$$

According to Clark (1989), the unemployment gap u_t^g is driven by the current and lagged output gap, *i.e.*,

$$u_t^g = \eta_0 y_t^g + \eta_1 y_{t-1}^g$$

Thus we see that

$$u_t - u_{t-1} = \eta_0 \left(y_t^g - y_{t-1}^g\right) + \eta_1 \left(y_{t-1}^g - y_{t-2}^g\right) + \varepsilon_t^u =: \eta_0 \Delta y_t^g + \eta_1 \Delta y_{t-1}^g + \varepsilon_t^u$$

Since in practice, u_t is in percentage while Δy_t^g is real number, hence when utilizing this measurement equation, we should multiply the right-hand side by 100:

$$u_t - u_{t-1} = 100 \left(\eta_0 \Delta y_t^g + \eta_1 \Delta y_{t-1}^g + \varepsilon_t^u\right) \tag{2.3}$$

Second, recall the definition of output gap, $y_t = y_t^n + y_t^g$, and the random walk process of y_t^n, $y_t^n = \mu + y_{t-1}^n + \varepsilon_t^n$. We notice that

$$y_t - y_{t-1} = \log(Y_t) - \log(Y_{t-1}) = y_t^g - y_{t-1}^g + (y_t^n - y_{t-1}^n) = \Delta y_t^g + \mu + \varepsilon_t^n$$

Since we will use quarterly data to run estimation, and in order to transform the log-difference into annualized increase, we multiply 400 on both sides and get

$$400\left[\log(Y_t) - \log(Y_{t-1})\right] = 400\left(\Delta y_t^g + \varepsilon_t^n\right) + 400\mu =: 400\left(\Delta y_t^g + \varepsilon_t^n\right) + \mu_y \tag{2.4}$$

where we defined that $\mu_y = 400\mu$.

Next, Recall that we have defined $\pi_t = \log(\Pi_t) - \log(\overline{\Pi})$. The steady state $\overline{\Pi}$ is invariant over time, and thus can be treated as a constant in our model. Define $\pi_e := \log(\overline{\Pi})$, and we have

$$\log(P_t) - \log(P_{t-1}) = \log(\Pi_t) = \pi_t + \log(\overline{\Pi}) = \pi_t + \pi_e$$

Again, transform the log-difference into annualized increase, and we get

$$400\left[\log(P_t) - \log(P_{t-1})\right] = 400\pi_t + \mu_\pi \tag{2.5}$$

where we defined that $\mu_\pi := 400\pi_e$.

Finally, Cui *et al.* provides also the following measurement equation based on the one-year-ahead inflation expectation (for the next year):

$$\Pi_t^{e4} = 100\left[\xi_0^e y_t^g + \xi_1^e y_{t-1}^g + \frac{(1-\theta_2^5)\theta_2}{1-\theta_2}\pi_t + \varepsilon_t^e\right] + \mu_\pi^e + \mu_\pi \tag{2.6}$$

where the constant μ_π^e represents the sample survey systematic difference from the model, and $\varepsilon_t^e \sim \mathcal{N}(0, \sigma_e^2)$ is the measurement error. We will use the quarterly survey data to get the inflation expectation. The superscript "4" in Π_t^{e4} reminds us that the inflation expectation should be processed into such way that represents the expected inflation for the next 12 months.

The equations (2.3) – (2.6) serve as the "measurement equations."

2.3 The State-Space Representation

In order to facilitate the use of Kalman filter to get the unobservable data and the use of Bayesian methods for parameter inference, we need a state-space representation of our model. For the state equations, we re-write the equation (2.2) as

$$\pi_t - \theta_0 y_t^g = \theta_1 y_{t-1}^g + \theta_2 \pi_{t-1} + \varepsilon_t^\pi \tag{2.7}$$

Then we can combine the state equations (2.1) and (2.7) in the following way

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -\theta_0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_t^g \\ y_{t-1}^g \\ y_{t-2}^g \\ \pi_t \end{bmatrix} = \begin{bmatrix} \rho_1 & \rho_2 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \theta_1 & 0 & 0 & \theta_2 \end{bmatrix} \begin{bmatrix} y_{t-1}^g \\ y_{t-2}^g \\ y_{t-3}^g \\ \pi_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^g \\ 0 \\ 0 \\ \varepsilon_t^\pi \end{bmatrix} \tag{2.8}$$

Here we denote $s_t := \left(y_t^g, y_{t-1}^g, y_{t-2}^g, \pi_t\right)^T$ and $\varepsilon_t := (\varepsilon_t^g, 0, 0, \varepsilon_t^\pi)^T$. Furthermore, denote

$$C := \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -\theta_0 & 0 & 0 & 1 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & 0 & 0 & -\theta_0^{-1} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad A := C \begin{bmatrix} \rho_1 & \rho_2 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \theta_1 & 0 & 0 & \theta_2 \end{bmatrix}$$

Then we can re-write the equation (2.8) as

$$s_t = A\, s_{t-1} + C\, \varepsilon_t \tag{2.9}$$

The covariance matrix of the error term $C\varepsilon_t$ can be represented as

$$\Omega := \mathrm{Var}(C\varepsilon_t) = C \begin{bmatrix} \sigma_g^2 & 0 & 0 & \sigma_{g\pi} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \sigma_{\pi g} & 0 & 0 & \sigma_\pi^2 \end{bmatrix} C^T$$

where we defined that $\sigma_{g\pi} := \mathrm{Cov}(\varepsilon_t^g, \varepsilon_t^\pi)$.

For the measurement equations, we can combine the equations (2.3) – (2.6) in the following way

$$\begin{bmatrix} u_t - u_{t-1} \\ 400\left[\log(Y_t) - \log(Y_{t-1})\right] \\ 400\left[\log(P_t) - \log(P_{t-1})\right] \\ \Pi_t^{e4} \end{bmatrix} = \begin{bmatrix} 100\eta_0 & 100(\eta_1 - \eta_0) & -100\eta_1 & 0 \\ 400 & -400 & 0 & 0 \\ 0 & 0 & 0 & 400 \\ 100\xi_0^e & 100\xi_1^e & 0 & \frac{100\left(1-\theta_2^5\right)\theta_2}{1-\theta_2} \end{bmatrix} \begin{bmatrix} y_t^g \\ y_{t-1}^g \\ y_{t-2}^g \\ \pi_t \end{bmatrix}$$

$$+ \begin{bmatrix} 0 \\ \mu_y \\ \mu_\pi \\ \mu_\pi + \mu_\pi^e \end{bmatrix} + \begin{bmatrix} 100\varepsilon_t^u \\ 400\varepsilon_t^n \\ 0 \\ 100\varepsilon_t^e \end{bmatrix}$$

Define

$$\mathcal{Y}_t := \begin{bmatrix} u_t - u_{t-1} \\ 400\left[\log(Y_t) - \log(Y_{t-1})\right] \\ 400\left[\log(P_t) - \log(P_{t-1})\right] \\ \Pi_t^{e4} \end{bmatrix}, \quad H := \begin{bmatrix} 100\eta_0 & 100(\eta_1 - \eta_0) & -100\eta_1 & 0 \\ 400 & -400 & 0 & 0 \\ 0 & 0 & 0 & 400 \\ 100\xi_0^e & 100\xi_1^e & 0 & \frac{100\left(1-\theta_2^5\right)\theta_2}{1-\theta_2} \end{bmatrix}$$

and $B := (0\,,\, \mu_y\,,\, \mu_\pi\,,\, \mu_\pi + \mu_\pi^e)^T$, $\nu_t := (100\varepsilon_t^u\,,\, 400\varepsilon_t^n\,,\, 0\,,\, 100\varepsilon_t^e)^T$, we can abbreviate the above matrix equation as

$$\mathcal{Y}_t = Hs_t + B + \nu_t \tag{2.10}$$

The covariance matrix of the error term ν_t can be represented as

$$\Sigma := \mathrm{Cov}(\nu_t) = \mathrm{E}\left[\nu_t \nu_t^T\right] = \begin{bmatrix} 10^4\,\sigma_u^2 & \left(4\times 10^4\right)\sigma_{un} & 0 & 0 \\ \left(4\times 10^4\right)\sigma_{nu} & \left(1.6\times 10^5\right)\sigma_n^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix} \tag{2.11}$$

where we defined $\sigma_{un} = \sigma_{nu} := \mathrm{Cov}(\varepsilon_t^u, \varepsilon_t^n) = \mathrm{Cov}(\varepsilon_t^n, \varepsilon_t^u)$. The definitions of σ_u^2, σ_n^2 and σ_e^2 follow from the previous subsection. Furthermore, we assumed that there is no correlation between structural shocks and the measurement error of the inflation expectation.

We will estimate the following parameters: $\alpha, \zeta, \mu_y, \mu_\pi, \rho_1, \rho_2, \eta_0, \eta_1,$ [2] and the covariance

[2] For other parameters, either we can use the parametric relationships mentioned ealier to infer from the estimated parameters, or can we use results from other's work.

matrix

$$\begin{bmatrix} \sigma_n^2 & \sigma_{ng} & \sigma_{nu} & \sigma_{n\pi} & 0 \\ \sigma_{gn} & \sigma_g^2 & \sigma_{gu} & \sigma_{g\pi} & 0 \\ \sigma_{un} & \sigma_{ug} & \sigma_u^2 & \sigma_{u\pi} & 0 \\ \sigma_{\pi n} & \sigma_{\pi g} & \sigma_{\pi u} & \sigma_\pi^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

Later we will report correlations instead of covariances in the above matrix, namely, we will report $\rho_{ng}, \rho_{nu}, \rho_{u\pi}, \rho_{gu}, \rho_{g\pi}$ and $\rho_{u\pi}$, instead of $\sigma_{ng}, \sigma_{nu}, \sigma_{u\pi}, \sigma_{gu}, \sigma_{g\pi}$ and $\sigma_{u\pi}$. The inference on the models (2.9) and (2.10) requires the implementation of Kalman filter and Markov Chain Monte Carlo (MCMC). In the subsequent section, we will briefly review those two methods, before implmenting them on the European data.

3 Theoretical Foundations of Bayesian Inference

In this section, we review the theories and methods of Bayesian inference in estimating DSGE models. There are reasons why we want to use Bayesian methods to estimate DSGE models. According to An and Schorfheide (2007), the Bayesian inference of DSGE models has three characteristics: first, compared to GMM estimation, Bayesian estimation is system-based; Second, the estimation is based on the likelihood function generated by the DSGE model, rather than the discrepancy between model-implied impulse responses and VAR impulse responses; And third, prior distributions can be used to incorporate additional information into the parameter estimation.

3.1 Basics of Bayesian Inference

The Bayesian inference for the parameter θ (θ may be vector) of a model starts with the specification of a prior distribution for the parameter, denoted as $p(\theta)$. This prior distribution reflects our prior knowledge about the parameter before starting statistical inference, which may come from rational guess, or the results of other similar statistical inference, *etc.* The (statistical) model is the (conditional) sample likelihood function $f(y|\theta)$, where y is sample vector or matrix. According to the Bayes' rule, the posterior distribution of the parameter θ, conditional on the sample, could be formulated as

$$f(\theta|y) = \frac{p(\theta)f(y|\theta)}{f(y)} \tag{3.1}$$

After the model being specified, and the sample being observed, $f(y)$ is independent of the choices of prior distributions. Therefore, we can also represent the equation (3.1) more concisely as

$$f(\theta|y) \propto p(\theta)f(y|\theta) \tag{3.2}$$

Note that there is no general requirement on which prior should be chosen, but theories do suggest to choose the "conjugated" prior in order to make the convergence faster. The *conjugated* prior is the prior distribution of parameter which, after combined with observations, has the same type of distribution as the posterior. For example, if our model $f(y|\theta)$ is the Poisson distribution, we can choose the gamma distribution as our "conjugated" prior for the mean parameter λ; and if we have a normal model $f(y|\theta) \sim \mathcal{N}(\mu, \sigma^2)$, then the conjugated prior for μ is normal distribution, while that for σ^2 is inverse-gamma distribution.

When doing Bayesian inference, it is usually the moments of the posterior distribution $f(\theta|y)$ that interest us. But most of the times, especially when estimating DSGE models, the posterior distribution is very complicated, such that moments can not be derived directly from the posterior. In this case, we need to use Monte Carlo methods to draw a sample that has the same distribution as the posterior, and use this sample to determine the posterior moments. In the next subsection, we will review such methods.

3.2 Markov Chain Monte Carlo (MCMC) Methods

The class of simulation techniques known as *Markov Chain Monte Carlo* (MCMC) methods permits one to simulate a dependent sequence of random draws from very complicated stochastic models. Here, our main emphasis will be placed on two MCMC methods, the first of which is known as the *Gibbs sampler*, which is a special case of the *Metropolis-Hasting algorithm*. But before we start, it is ideal to shortly review the basic concepts of Markov Chain theory.

A *Markov chain* is a collection of random variables $\{Y_0, Y_1, \cdots, Y_n\}$ in $\mathbb{R}^k$, $k \in \mathbb{N}_+$, which is governed by the transition probabilities

$$\mathrm{P}(Y_{n+1} \in A \,|Y_0, \cdots, Y_n) = h(Y_n, A) \tag{3.3}$$

where A belongs to the support of the random variable Y_{n+1}, and $h(\bullet)$ denotes any function that depends only on Y_n and the range A. The property (3.3) is known as *Markov property*.

Moreover, the distribution of Y_0 is known as the *initial distribution* of the Markov chain. The conditional distribution of Y_n given Y_0 is described by

$$\mathrm{P}(Y_n \in A \,|Y_0) = h^n(Y_0, A) \tag{3.4}$$

where $h^n(\bullet)$ stands for the n-th application of $h(\bullet)$. An *invariant distribution* $\pi(y)$ for the Markov chain is a density satisfying

$$\pi(A) = \int h(y, A)\pi(y)\,\mathrm{d}y \tag{3.5}$$

and it is also an equilibrium distribution if

$$\lim_{n\to\infty} h^n(y, A) = \pi(A) \tag{3.6}$$

Here, we use $\pi(y)$ to denote both the invariant distribution or density of a random variable. A Markov chain with invariant distribution $\pi(y)$ is *irreducible* if for any initial value Y_0, it has a positive probability of entering any state that is assigned with positive probability by $\pi(y)$. A Markov chain is *periodic*, if it can take on certain values only at regularly spaced intervals. If a Markov chain with a proper invariant distribution is both irreducible and aperiodic, then the invariant distribution is unique and it is also the equilibrium distribution of the chain.

The idea of MCMC algorithm is to construct a transition kernel, denoted by $p(y_1, y_2)$, both y_1 and y_2 are possibly vectors with the same dimension, which has an invariant distribution (density) that is equal to the target density $\pi(y)$. After such a transition kernel being constructed, we can start our process at an initial value $y^{(0)}$, and yeild a draw $y^{(1)}$ from the kernel density $p(y^{(0)}, y^{(1)})$; Then $y^{(2)}$ could be drawn from the kernel density $p(y^{(1)}, y^{(2)})$. Continuing on this process, we could draw $y^{(n)}$ from $p(y^{(n-1)}, y^{(n)})$. The distribution of $y^{(n)}$ is approximately equal to the target distribution after a transient period. Therefore, MCMC algorithms provide an approximation to the exact posterior distribution of a parameter. However, the problem arises regarding how to find a kernel that has the target density as its invariant distribution.

Suppose we want to sample from a joint distribution with two random variables $f(x, y)$, both of the two variables may be vectors. We further assume that the two conditional distributions $f(x|y)$ and $f(y|x)$ are known. The *Gibbs algorithm* with two blocks could be described as follows (Greenberg, 2008):

1. Choose a starting value $y^{(0)}$;

2. First iteration: draw $x^{(1)}$ from $f(x|y^{(0)})$, and $y^{(1)}$ from $f(y|x^{(1)})$;

   . . . .

n. n-th iteration: draw $x^{(n)}$ from $f(x|y^{(n-1)})$, and $y^{(n)}$ from $f(y|x^{(n)})$.

We continue on this process, until the desirable number of iterations is obtained. Since most of the times we arbitrarily choose our starting draw, therefore, some of the draws from the above process must be discarded. Those discarded draws are called *transient* or *burn-in* sample. The exact size of the burn-in sample could be determined by convergence diagnostics. It could be proved that the invariant distribution of the Gibbs kernel is indeed the target distribution (Tierney, 1994). The extension of the Gibbs algorithm to the n-block case is obvious.

Let n denote the number of total iterations, and m denote the size of the burn-in sample. The point estimator for the mean and the variance of the x are:

$$\widehat{\mu}_x := \frac{1}{n-m} \sum_{i=m+1}^{n} x^{(i)} \qquad \text{and} \qquad \widehat{\sigma}_x^2 = \frac{1}{n-m-1} \sum_{i=m+1}^{n} \left(x^{(i)} - \widehat{\mu}_x \right)^2 \tag{3.7}$$

The point estimator of the mean and the variance of the y are similar.

Metropolis-Hasting (MH) *algorithm* is more general than the Gibbs sampler because it does not require the availability of the full set of conditional distribution for sampling. For the one-block case, we want to generate a sample from $f(y)$, where y may be vector. We firstly introduce the idea of *reversible kernel*, which is defined as the transition kernel $q(y_1, y_2)$ such that

$$f(y_1)\, q(y_1, y_2) = f(y_2)\, q(y_2, y_1) \tag{3.8}$$

It could be proved that (Chib and Greenberg, 1995) if $q(y_1, y_2)$ is reversible, then

$$\mathrm{P}(y \in A) = \int_A f(y)\, \mathrm{d}y \tag{3.9}$$

which means that $f(y)$ is the invariant distribution for the kernel $q(y_1, y_2)$. The trick of the MH algorithm is to start with an irreversible *proposal kernel*, and make the irreversible kernel reversible. Suppose that our proposal kernel $p(y_1, y_2)$ is not reversible, then for some pairs (y_1, y_2) we have

$$f(y_1)\, p(y_1, y_2) > f(y_2)\, p(y_2, y_1) \tag{3.10}$$

The MH algorithm multiplies the left-hand side of the equation (3.10) by a function $\alpha(y_1, y_2)$ and the right-hand side by $\alpha(y_2, y_1)$, that turns the irreversible kernel $p(y_1, y_2)$ into the reversible kernel $q(y_1, y_2) = \alpha(y_1, y_2)p(y_1, y_2)$:

$$f(y_1)\,\alpha(y_1, y_2)\,p(y_1, y_2) = f(y_2)\,\alpha(y_2, y_1)\,p(y_2, y_1) \tag{3.11}$$

where the function $\alpha(y_1, y_2)$ assigns the probability of moving from y_1 (otherwise the process won't move and stay at y_1), and the function $\alpha(y_2, y_1)$ has the similar interpretation. Our next problem is to find the function $\alpha(\bullet)$. Keeping the condition (3.10), we could set the $\alpha(y_2, y_1)$ in the equation (3.11) as 1, then from (3.11), we solve

$$\alpha(y_1, y_2) = \frac{f(y_2)\,p(y_2, y_1)}{f(y_1)\,p(y_1, y_2)} < 1 \tag{3.12}$$

where it is required that $f(y_1)\,p(y_1, y_2) \neq 0$. Therefore, by letting $\alpha(y_1, y_2) < \alpha(y_2, y_1)$, we have equalized the probability that the kernel goes from y_1 to y_2 with the probability that the kernel goes from y_2 to y_1. This provides us with the following algorithm (Greenberg, 2008):

1. Given y_1, generate y_2 from the proposal transition kernel $p(y_1, y_2)$;

2. Draw a number U from the uniform distribution $U(0, 1)$. If

$$U \leq \alpha(y_1, y_2) = \min\left\{\frac{f(y_2)\,p(y_2, y_1)}{f(y_1)\,p(y_1, y_2)}, 1\right\}$$

   Then return y_2. Otherwise, return y_1 and go back to the first step above. Note that in Dynare, $\alpha(y_1, y_2)$ is called the *acceptance rate.*

   . . . .

n. Draw until the desirable number of iterations is obtained.

Note that in practice, the performance of the algorithm will obviously strongly depend on the choice of proposal kernel.

In Bayesian inference, it is the posterior distribution $f(\theta|y)$ from which we would like to draw sample. In such a case, when calculating the acceptance rate (3.12), only prior distribution $p(\theta)$ and the (conditional) sample likelihood function $f(y|\theta)$ are needed. The normalization constant $f(y)$ would be canceled out from division.

3.3 The Kalman Filter

The Kalman filter is used in the situation where there are hidden variables existing in the model. In such a situation, we can use the Kalman filter to "simulate" observations for the hidden variables, based on the observable variables. The Kalman filter is based on the the recursive state space model. We firstly define the *transition equation* (which functions similarly as the transition kernels introduced above, but now it has a specific functional form) as

$$x_t = a_t + B_t x_{t-1} + C_t \varepsilon_t \ , \qquad \varepsilon_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Sigma_t) \tag{3.13}$$

where x_t is an unobservable state vector, a_t is a deteministic vector, and B_t, C_t, Σ_t are time-variant matrices. Moreover, we define a *measurement equation* as

$$y_t = d_t + F_t x_t + \nu_t \ , \qquad \nu_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Omega_t) \tag{3.14}$$

where y_t is observable vector, d_t is a deterministic vector, and F_t, Ω_t are matrices. For the recursive state space model defined in the equation (3.13) and (3.14), we assume that

$$\mathrm{E}(\nu_t \varepsilon_t^T) = 0 \ , \qquad \mathrm{E}(\varepsilon_t x_0^T) = 0 \ , \qquad \mathrm{E}(\nu_t x_0^T) = 0 \tag{3.15}$$

We notice that under the assumption (3.15), from the equation (3.13), we have

$$\mathrm{E}(x_t) = a_t + B_t \mathrm{E}(x_{t-1}) + C_t \mathrm{E}(\varepsilon_t) = a_t + B_t \mathrm{E}(x_{t-1}) =: \mathrm{E}(x_{t|t-1}) \tag{3.16}$$

$$\mathrm{Var}(x_t) = B_t \mathrm{Var}(x_{t-1}) B_t^T + C_t \Sigma_t C_t^T =: \mathrm{V}_{t|t-1} \tag{3.17}$$

With the notations introduced by the equations (3.16) and (3.17), we can combine the recursive state space model (3.13) and (3.14) by the following matrix:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mathrm{E}(x_{t|t-1}) \\ d_t + F_t \mathrm{E}(x_{t|t-1}) \end{bmatrix} , \begin{bmatrix} \mathrm{V}_{t|t-1} & \mathrm{V}_{t|t-1} F_t^T \\ F_t \mathrm{V}_{t|t-1} & F_t \mathrm{V}_{t|t-1} F_t^T + \Omega_t \end{bmatrix} \right) \tag{3.18}$$

Using the property of multivariate normal distribution, we see that

$$\mathrm{E}(x_t | y_t) = \mathrm{E}(x_{t|t-1}) + \mathrm{V}_{t|t-1} F_t^T \left(F_t \mathrm{V}_{t|t-1} F_t^T + \Omega_t \right)^{-1} \left[y_t - \left(F_t \mathrm{E}(x_{t|t-1}) + d_t \right) \right] \tag{3.19}$$

$$\mathrm{Var}(x_t | y_t) = \mathrm{V}_{t|t-1} - \mathrm{V}_{t|t-1} F_t^T \left(F_t \mathrm{V}_{t|t-1} F_t^T + \Omega_t \right)^{-1} F_t \mathrm{V}_{t|t-1} \tag{3.20}$$

We have the following algorithm for generating and updating the hidden variable x_t:

1. Choose the initial expectation $\mathrm{E}(x_0)$, and the initial variance V_0. Draw a starting value x_0 from the distribution $\mathcal{N}(\mathrm{E}(x_0), \mathrm{V}_0)$.

2. With the observation y_1, we can use the equations (3.19) and (3.20) to calculate $\mathrm{E}(x_1|y_1)$ and $\mathrm{V}_1 := \mathrm{Var}(x_1|y_1)$, where we set $\mathrm{E}(x_t|x_{t-1}) = \mathrm{E}(x_0)$, $\mathrm{V}_{t|t-1} = \mathrm{V}_0$.

3. Draw the value x_1 from the distribution $\mathcal{N}\left(\mathrm{E}(x_1|y_1), \mathrm{V}_1\right)$.

4. With the observation y_2, we use the equations (3.19) and (3.20) to calculate $\mathrm{E}(x_2|y_2)$ and $\mathrm{V}_2 := \mathrm{Var}(x_2|y_2)$.

   . . . .

n. Draw until the desirable number of iterations is obtained.

3.4 Bayesian Estimating Algorithm for DSGE Models

Recall from the basic Bayesian statistics that the posterior distribution is propotional to the prior distribution and the (conditional) sample likelihood function:

$$f(\theta|y) \propto f(y|\theta)\, p(\theta) \tag{3.21}$$

where $p(\theta)$ denotes the prior distribution (density function or probability mass function). Note that the parameter θ may be vector, and y is the sample vector (or matrix).

When estimating DSGE models, most likely it is the posterior moments which we would be interested to infer. In order to determine the estimates of posterior moments, we use the *random walk Metropolis* (RWM) algorithm to draw sample from the posterior distribution $f(\theta|y)$. The RWM algorithm is provided in the following (An and Schorfheide, 2007):

1. Initialize the algorithm with an arbitrary value θ_0, and set $i = 1$.

2. Draw θ_i^* from $\theta_i^* = \theta_{i-1} + \varepsilon$, where ε is normally distributed, *i.e.*, $\varepsilon \sim \mathcal{N}\left(0, \Sigma\right)$.

3. Draw a number U from the uniform distribution $U(0, 1)$, and if

$$U \leq \alpha\left(\theta_{i-1}, \theta_i^*\right) = \min\left\{\frac{f(y|\theta_i^*)\, p(\theta_i^*)}{f(y|\theta_{i-1})\, p(\theta_{i-1})}\,, 1\right\}$$

return $\theta_i = \theta_i^*$; otherwise, return $\theta_i = \theta_{i-1}$ and go back to the step 2.

. . . .

n. Draw until the desirable number of iterations is obtained.

Note that the Kalman filter will be used to evaluate the likelihood $f(y|\theta_i^*)$ and $f(y|\theta_{i-1})$.

4 Results of Estimation

4.1 Data Description and Priors

In this thesis, quarterly data are used for estimation. The main observed variables are quarterly output (GDP), unemployment rate, price level, and survey of inflation expectation. Most data for this thesis come from St.Louis databank (http://research.stlouisfed.org/fred2/). For some countries (Estonia, Malta, *etc.*) where suitable quarterly CPI data are hard to find, HICP are used instead, which come from the Eurostat (http://epp.eurostat.ec.europa.eu/).

The estimation is done in two cases, without inflation expectation data and with inflation expectation data. In the former case, the Kalman filter is used (based on the equation (2.6)) to produce "artificial" data of inflation expectation. In the latter case, we firstly transform the survey data into expected inflation rate, then use the produced expected inflation rate to implement the estimation.

The question asked for the survey data is "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will (++) increase more rapidly, or (+) increase at the same rate, or (=) increase at a slower rate, or (−) stay about the same, or (−−) fall, or (N) don't know." If there are P_1, P_2, P_3, P_4, P_5, P_6 shares of respondents answering ++, +, =, −, −−, and N respectively, the indicator would be

$$\text{Survey indicator} = 1 \times P_1 + 0.5 \times P_2 + 0 \times P_3 - 0.5 \times P_4 - 1 \times P_5$$

An indicator of 0.5 means that the average expected inflation rate for the next 12 months would be the same as the inflation rate of the last 12 months, while an indicator of -0.5 means that the average expected inflation rate for the next 12 months would be 0. We can thus transform the survey indicator into the expected inflation rate in the following way: [3]

$$\Pi_t^{e4} = \frac{\text{indicator value}}{\text{indicator value} - (-50)} \times \text{average of the inflation rates over the past 4 quarters}$$

There will be systematic difference between (annualized) inflation rate and the expected inflation rate Π_t^{e4}. One reason of which is because the inflation rate reflects only one quarter, while Π_t^{e4} is calculated over 4 quarters. However, the constant term μ_π^e in the equation (2.6) will eliminate this systematic difference.

In estimation, the parameters β and κ will be kept at their calibrated values, since we cannot get reliable estimates for the two parameters. The parameter β should be the inverse of the real interest rate, and Mehra and Prescott (1985) provided an approximation of historical real interest rate of around 4% annually, which can be translated into $\beta = 0.99$ with our quarterly data. Moreover, following Cui *et al.*, the value of κ will be set as $\kappa = 4$.

We now look at the priors. The parameter α indicates the frequency of the average price adjustment. Gali and Gertler (1999) pointed out that the average frequency of adjustment should be between 3 and 6 quarters. We take the number in between, *i.e.*, $1/(1-\alpha) = 4$ quarters, which gives us a prior of $\alpha = 0.75$. Further assume that the prior of α is normal. Furthermore, Cui *et al.* provided Gamma priors for ζ, μ_y and μ_π with centers of 0.5, 3.06, and 3.06 respectively. For μ_π^e, we use the difference between the average inflation rate and the average on the expected inflation rate.

Based on the results of Basistha and Nelson (2007), the prior of ρ_1 should be centered around 1.35, while that of ρ_2 be around -0.5. We will assume that the priors are normally distributed for the two parameters. For other parameters, we use the parameter settings of Cui *et al.*, which can be read from the Table 2 – 49 (with some minor changes as marked in red).

4.2 Estimation Results without Survey Data

We firstly present the results of estimation without using the inflation expectation data. The results of Bayesian inference on parameters can be read from the Tables 4 – 31 in the Appendix B.

Recall that the parameter ζ measures the elasticity of the indexation to past inflation.

[3] In the following, all inflation rates are taken as log-differences of price levels.

Generally, a ζ that is smaller than 0.5 implies a small degree of inflation persistence. From the estimation results we see that most countries fall into the category in which past inflation has little effect on future ones. However, Italy, Finland, Hungary and Romania are exceptions, indicating a strong persistence of inflation in those countries. Later we will see that when estimated with survey data, even those four countries have ζ's that are significantly less than 0.5.[4] For the AR(2) process of the equation (2.1), our estimation results show that the values of ρ_1 are between 1.3 and 1.4, and that of ρ_2 are between -0.5 and -0.3. The sums of ρ_1 and ρ_2 are between 0.8 and 0.9, indicating the persistence of output gap across EU-member states. The finding on the parameter η_0 is somehow interesting: The Okun's law states that an 1% drop of unemployment rate today can increase today's output by 2%. Based on the equation (2.3), this implies that $\eta_0 \approx -0.5$. However, from our estimation, a lot of countries have η_0's that strongly deviate -0.5. Moreover, the countries with η_0 significantly lower than -0.5 tend to be those with relatively strong economy (Germany, Finland, Denmark, Ireland, UK, *etc.*), while countries with $\eta_0 > -0.5$ significantly tend to be those with relatively weak economy (Portugal, Greece, Poland, Crotia, Estonia, Hungary, Malta, Slovenia, *etc.*).

Figures 29 – 56 in the Appendix C show the estimation of NAIRU. The red curve is the actual unemployment rate, the blue- and black-dotted curves show NAIRU and it's 95% confidence interval respectively, and the grey curve traces the dynamics of inflation. We see that generally, when NAIRU drops below the actual unemployment rate, the inflation rate goes up, and *vice versa*, indicating a significant relationship between unemployment gap and inflation. To confirm this, we calculate the Pearson's correlation between unemployment gap (mean of u_t^g) and inflation rate for each country. The results can be read from the Table 2 below:

Comparing with the Table 1, we see that our method of depicting the interactivity between unemployment and inflation performs better than that of King and Watson's. The majority of countries have significantly negative correlation, with the only "outlier" of Italy. [5] Observing the Figures 29 – 56, one notices that in some countries (Bulgaria, Croatia, Hungary, Ireland, Italy, Lithuania, Malta, *etc.*) NAIRU traces the actual unemployment rate

[4] To be precisely, ζ-estimates for three out of those four countries will be significantly less than 0.5. Romania will be dropped from estimation with survey data, since the survey data for Romania cannot be obtained reliably.

[5] One may notice that in the Table 1, we use monthly data, while the data used for producing Table 2 and Table 3 are of quarterly frequencies. It is because the output level can only be available per quarter. Although monthly data is better to trace the dynamic interactions of the time series, when output data are involved, we have no choice but to use quarterly data instead.

Country	Corr.	Time Horizon	Country	Corr.	Time Horizon
Austria	-0.5509^{**}	Q2.1960 – Q4.2013	Belgium	-0.8795^{**}	Q2.1970 – Q4.2013
Bulgaria	-0.3961^{**}	Q2.2000 – Q1.2014	Crotia	-0.4057^{**}	Q3.2000 – Q1.2014
Cyprus	-0.1739^{*}	Q2.2000 – Q1.2014	Czech Rup.	-0.4218^{**}	Q2.1995 – Q4.2013
Denmark	-0.6789^{**}	Q2.1970 – Q4.2013	Estonia	-0.6661^{**}	Q2.1997 – Q4.2013
Finland	-0.5822^{**}	Q2.1964 – Q4.2013	France	-0.9473^{**}	Q3.1969 – Q4.2013
Germany	-0.4132^{**}	Q1.1991 – Q4.2013	Greece	-0.1336	Q3.1998 – Q1.2013
Hungary	-0.6520^{**}	Q2.1995 – Q4.2013	Ireland	-0.7346^{**}	Q2.1983 – Q4.2013
Italy	0.1013	Q4.1979 – Q4.2013	Latvia	-0.6373^{**}	Q2.1998 – Q1.2014
Lithuania	-0.6701^{**}	Q2.1998 – Q1.2014	Luxembourg	-0.2666^{**}	Q2.1983 – Q4.2013
Malta	-0.0589	Q3.2000 – Q1.2014	Netherlands	-0.7773^{**}	Q2.1970 – Q4.2013
Poland	-0.8025^{**}	Q2.1995 – Q4.2013	Portugal	-0.8691^{**}	Q4.1983 – Q4.2013
Romania	-0.6631^{**}	Q4.2000 – Q1.2014	Slovakia	-0.3744^{**}	Q3.1993 – Q4.2013
Slovenia	-0.5869^{**}	Q2.1996 – Q4.2013	Spain	-0.8193^{**}	Q1.1978 – Q3.2013
Sweden	-0.7170^{**}	Q2.1970 – Q4.2013	UK	-0.1221^{**}	Q3.1991 – Q4.2013

Table 2: Pearson's Correlations between Inflation and Unemployment Gap (mean) (without survey data). * denotes 5%-significance; while ** denotes 1%-significance. The countries with positive correlations are marked in red.

very closely, making it difficult to use the unemployment gap to predict inflation; However, in some other countries (Czech Republic, Finland, Germany, Latvia, Sweden, UK, *etc.*), the unemployment gap is large and more persistent, and the trend of NAIRU is smoother than that of actual unemployment rate, making it possible to use the interaction between NAIRU and actual unemployment rate to predict (near) future inflation level.

The economic theory suggests that the output gaps and unemployment gaps should be negatively correlated. This is confirmed by the Figures 57 – 84 in the Appendix D, in which the two time series of estimated unemployment gap (red curve) and estimated output gap (gery-dotted curve) are drawn together. In general, large gaps imply that there are rooms for policy to stabilize the economy.

4.3 Estimation Results with Survey Data

In this subsection, we present our estimation results using the survey data. The results of Bayesian inference on parameters can be read from the Tables 32 – 51 in the Appendix E. Note that we estimate only 20 countries this time, the reason is either the reliable survey data for certain countries cannot be obtained, or the durations of the survey data for some countries are not enough for a reliable estimation.

With survey data, all the estimates for ζ are now significantly less than 0.5, including Italy, Finland, Hungary, *etc.*, which have $\zeta > 0.5$ when estimated without survey data. This indicates that the inflation rate across europe is less persistent. Furthermore, the estimation results for the parameters of the AR(2) process, ρ_1 and ρ_2, are similar compared with those without using survey data. The only difference is that now the estimates are less variable across countries. Finally, the estimates for η_0 are still not consistent to Okun's law for some countries, but the number of countries that disobey the Okun's law is less than that in the without-survey-data case, and the magnitudes of deviation are also less.

Figures 85 – 104 in the Appendix F show the estimation of NAIRU with survey data. As is in the last subsection, in general, the relationship between unemployment gap and inflation is significant. Compared with the previous results, the confidence intervals of NAIRU-estimates are smaller, which is resulted from the additional information coming from the new data. Moreover, the magnitudes of unemployment gap are much smaller in the case of using survey data. This drop of magnitudes is also confirmed by Cui, *et al.* in the US market. Again, we calculate the Pearson's correlation between unemployment gap (mean of u_t^g) and inflation

Country	Corr.	Time Horizon	Country	Corr.	Time Horizon
Austria	-0.1378	Q4.1995 – Q4.2013	Belgium	-0.1030	Q1.1985 – Q4.2013
Czech Rup.	-0.3595^{**}	Q2.1996 – Q4.2013	Denmark	-0.2359^{**}	Q1.1985 – Q4.2013
Finland	-0.2317^{**}	Q1.1996 – Q4.2013	France	-0.3503^{**}	Q1.1985 – Q4.2013
Germany	-0.2776^{**}	Q2.1992 – Q4.2013	Greece	0.0397	Q3.1999 – Q1.2013
Hungary	-0.5805^{**}	Q2.1996 – Q4.2013	Ireland	-0.3828^{**}	Q1.1985 – Q4.2013
Italy	-0.7810^{**}	Q2.1985 – Q4.2013	Luxembourg	-0.1508	Q1.2002 – Q4.2013
Netherlands	-0.3588^{**}	Q1.1985 – Q4.2013	Poland	-0.0019	Q1.2001 – Q4.2013
Portugal	-0.7215^{**}	Q2.1986 – Q4.2013	Slovakia	-0.3386^{**}	Q2.1999 – Q4.2013
Slovenia	-0.5170^{**}	Q2.1997 – Q4.2013	Spain	-0.3429^{**}	Q3.1986 – Q3.2013
Sweden	-0.1059	Q4.1995 – Q4.2013	UK	-0.4642^{**}	Q1.1985 – Q4.2013

Table 3: Pearson's Correlations between Inflation and Unemployment Gap (mean) (with survey data). * denotes 5%-significance; while ** denotes 1%-significance. The countries with positive correlations are marked in red.

rate for each country. The results can be read from the Table 3 below:

However, the negative correlations between unemployment gap and inflation rate are less significant compared with the results in the Table 2. The reasons may contain the following: (1) The durations of survey data are much shorter compared to other time series. Therefore, when estimating with survey data shorter time series are used, which creates unstability of estimates. The estimates are thus less reliable; (2) The economies of some countries (especially those in southern and eastern Europe) are unstable, so that the potential outputs for which are not unit roots. The estimates of NAIRU and unemployment gap for those countries may be not reliable based on our model.

Again, Figures 105 – 124 in the Appendix G confirm that the estimated output gaps and unemployment gaps are negatively correlated.

5 Summary and Further Research Proposals

In this thesis, a structual model with forward and backward looking Phillips curve is used to estimate the output gap and unemployment gap. The interaction of NAIRU and unemployment rate provides thus an alternative way of capturing the relationship between inflation and unemployment, *i.e.*, when NAIRU is below unemployment rate, in general the inflation will drop down, and *vise versa*. Our method is better than the King and Watson's method because: (1) There are fewer "abnomalities." Comparing Tables 2 – 3 with the Table 1, we see that by our method, although positive correlations still exist, they are not significant, and the number of which is also much less. (2) The Unemployment gaps for some countries are very persistent, making it possible to predict the inflation rate in the near future. (3) Gaps indicate the room for policy to stabilize economy.

Further works may be done in the future. First, one of the final objectives of this study is to enable prediction of inflation from NAIRU. Although having confirmed the relationship between unemployment gap and inflation, this thesis doesn't show that by how much the inflation will change given a certain amount of unemployment gap. From the figures in the Appendix we see that sometimes a turning point of unemployment gap results in a dramatic change of inflation, but sometimes the change is much subtle. Therefore, we have to gain further insights into the behavior of gaps and the factors that may influence inflations.

Second, this thesis does not consider the private agents' learning behavior of the information of the economy. Agents in the economy have learning processes through which the past inflation is related to the output of the economy. It is certainly worthwhile to make the model more sophiscated by considering this learning process.

Finally, this thesis considers only the private sector. To make the estimation more precise, one should also consider other economic sectors such as government. Besides, the central bank announcement of interest rate policy might also affect the learning process. Therefore, more sophiscated model with more sectors of economy may be proposed.

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A Filtered Time Series of Unemployment and Inflation Rate

We filtered the monthly time series of unemployment (red curve) and inflation rate (year-on-year based CPI, black curve) of the 28 EU-member states into 3 frequencies, namely, zero frequencies (top), business-cycle frequencies (18-60 months, middle), and high frequency (bottom). The figures for each country are presented in the following.

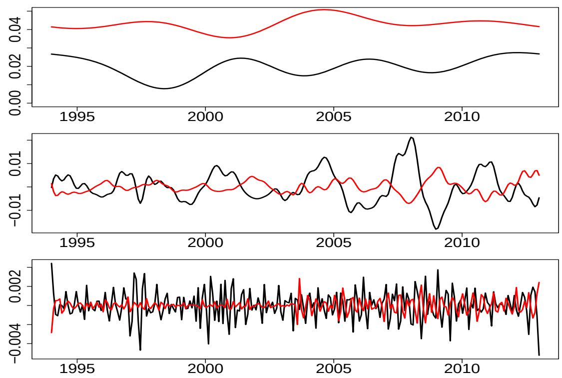

Figure 1: Filtered time series for Austria.

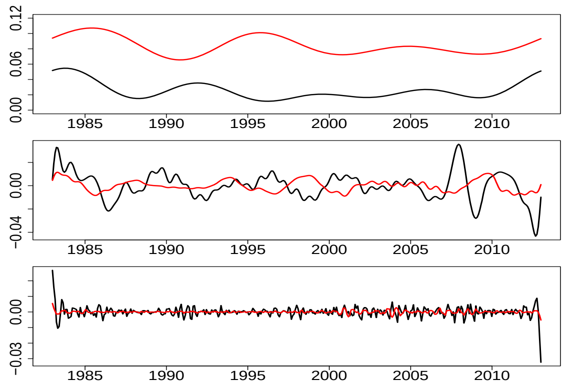

Figure 2: Filtered time series for Belgium.

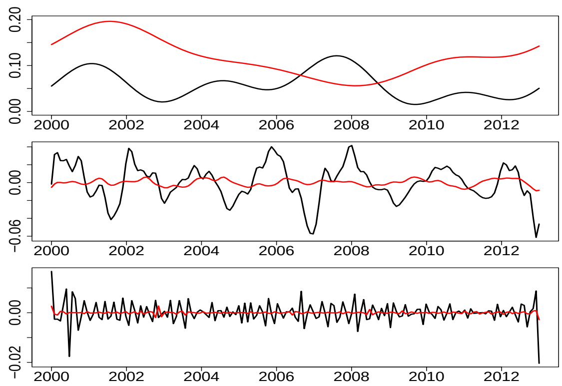

Figure 3: Filtered time series for Bulgaria.

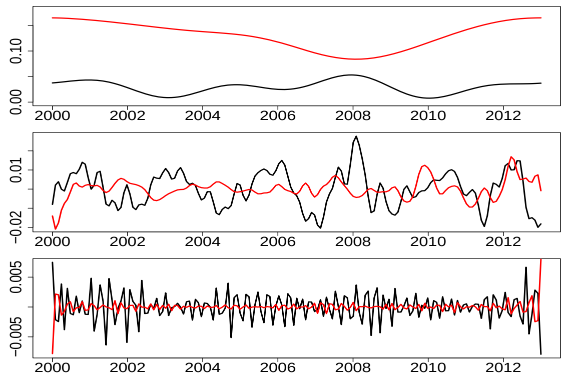

Figure 4: Filtered time series for Crotia.

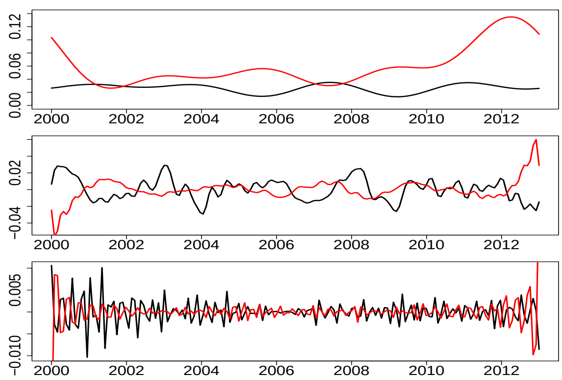

Figure 5: Filtered time series for Cyprus.

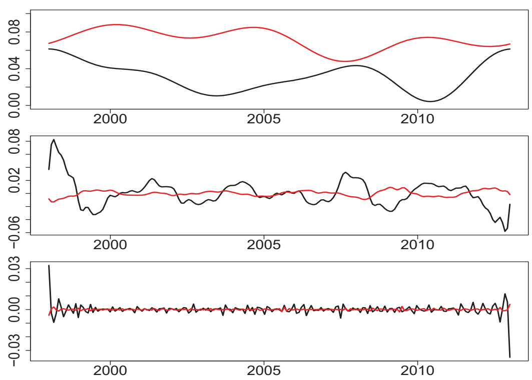

Figure 6: Filtered time series for Czech Rep.

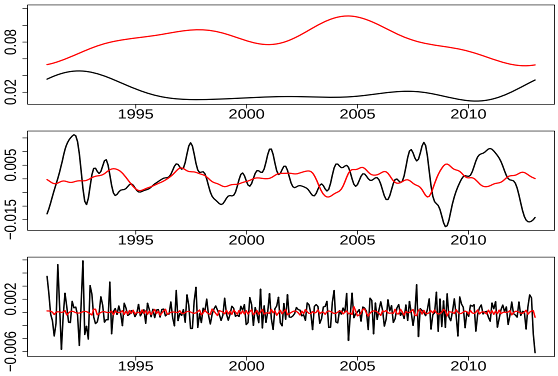

Figure 7: Filtered time series for Germany.

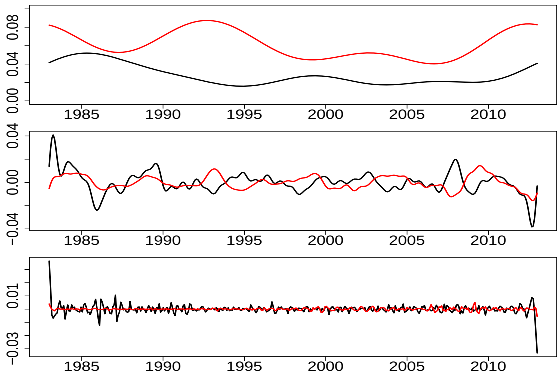

Figure 8: Filtered time series for Denmark.

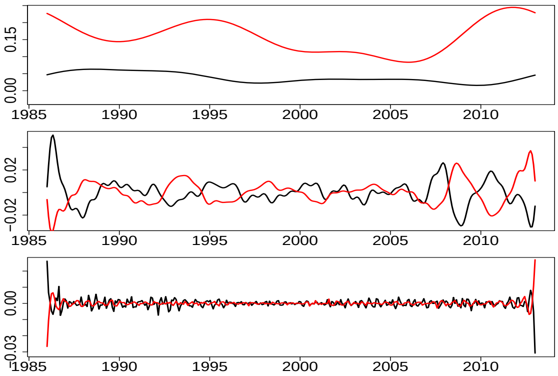

Figure 9: Filtered time series for Spain.

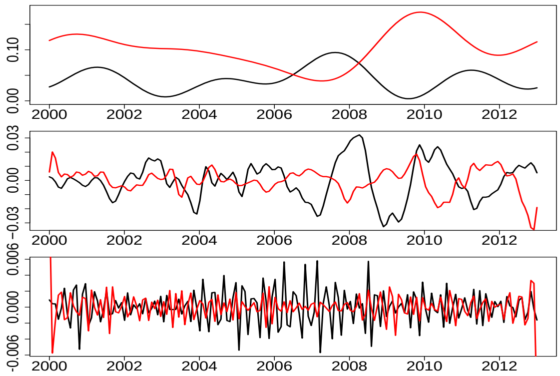

Figure 10: Filtered time series for Estonia.

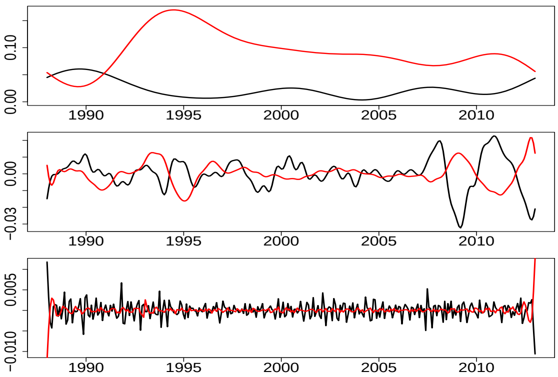

Figure 11: Filtered time series for Finland.

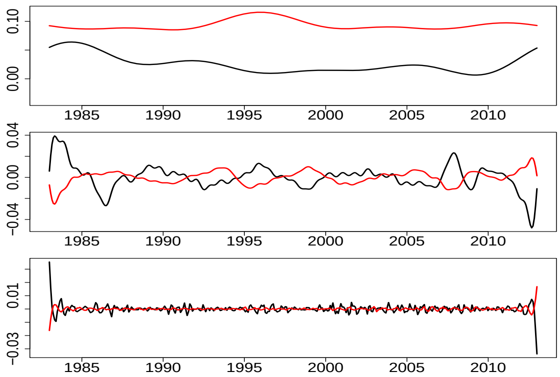

Figure 12: Filtered time series for France.

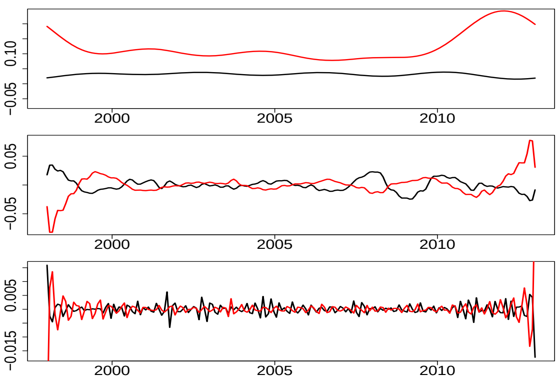

Figure 13: Filtered time series for Greece.

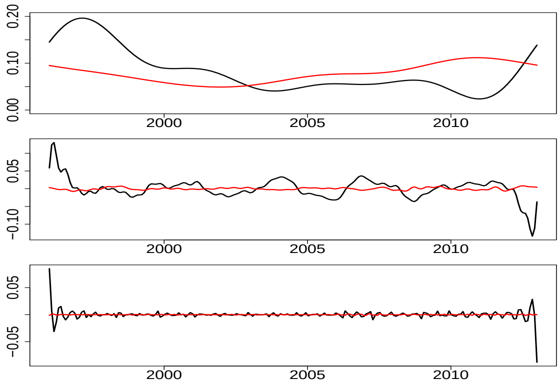

Figure 14: Filtered time series for Hungary.

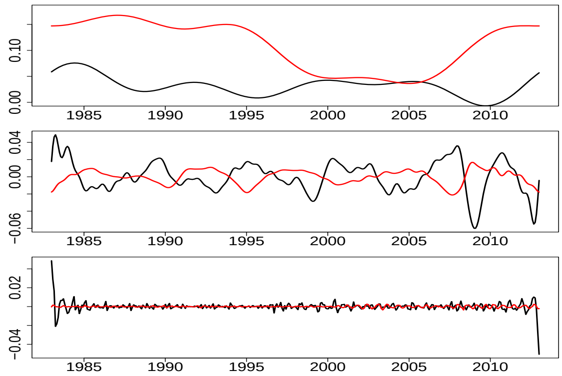

Figure 15: Filtered time series for Ireland.

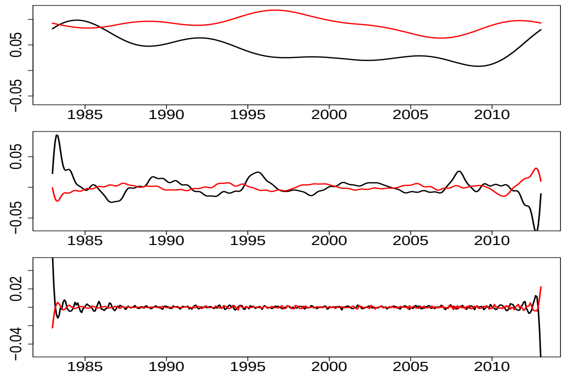

Figure 16: Filtered time series for Italy.

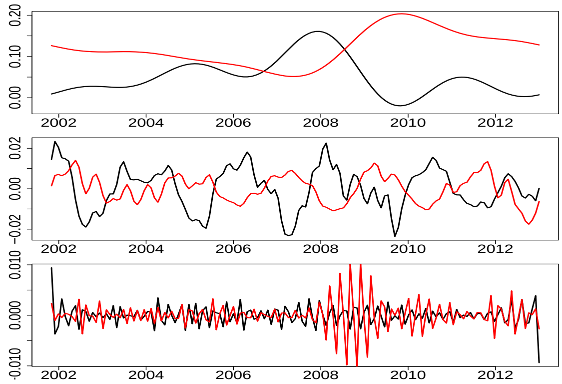

Figure 17: Filtered time series for Latvia.

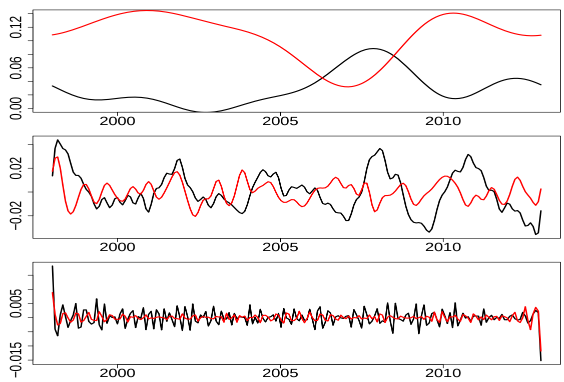

Figure 18: Filtered time series for Lithuania.

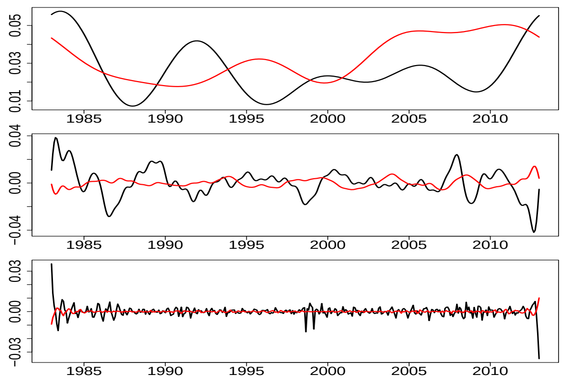

Figure 19: Filtered time series for Luxembourg.

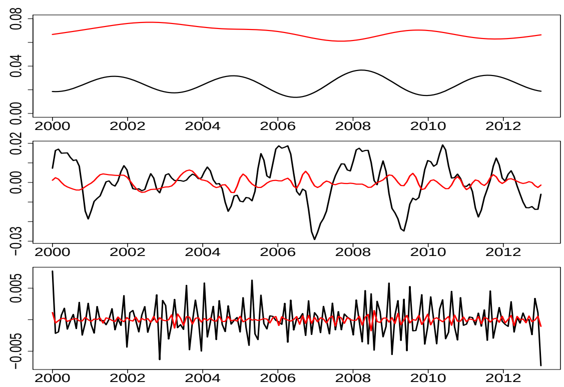

Figure 20: Filtered time series for Malta.

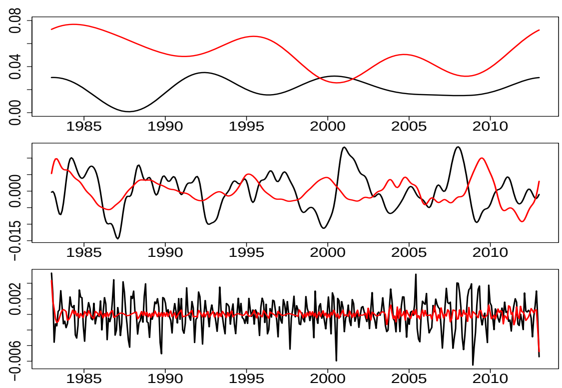

Figure 21: Filtered time series for Netherlands.

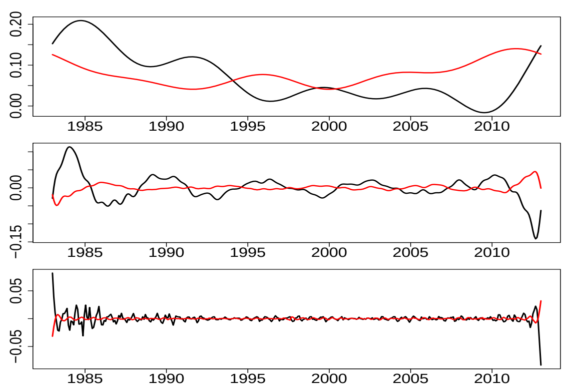

Figure 22: Filtered time series for Portugal.

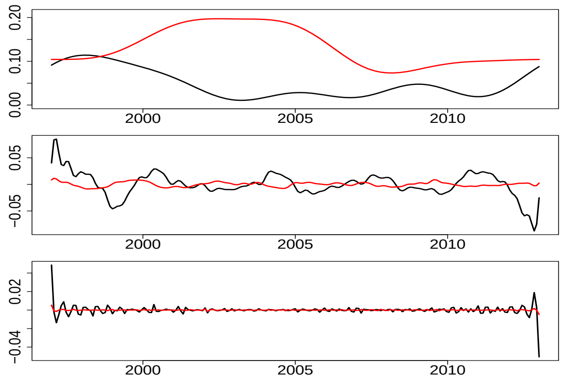

Figure 23: Filtered time series for Poland.

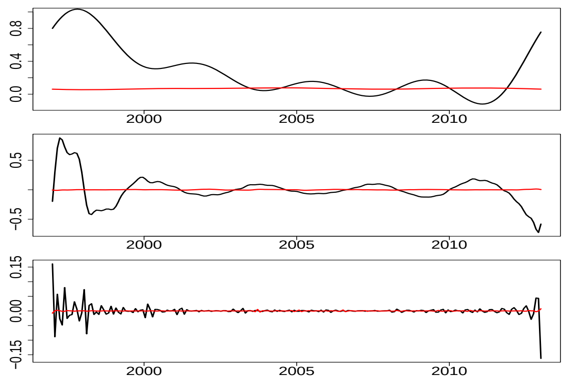

Figure 24: Filtered time series for Romania.

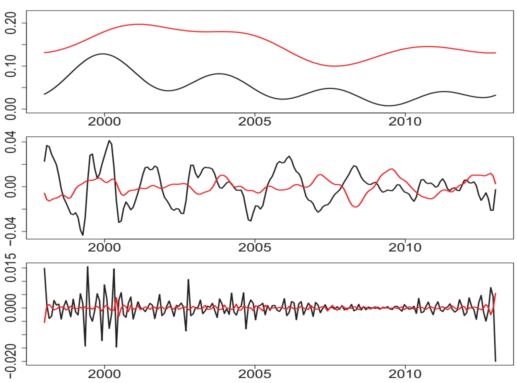

Figure 25: Filtered time series for Slovakia.

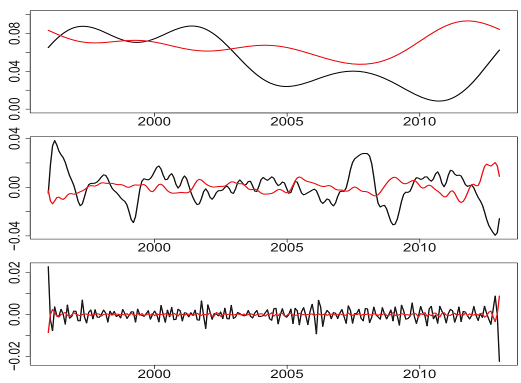

Figure 26: Filtered time series for Slovenia.

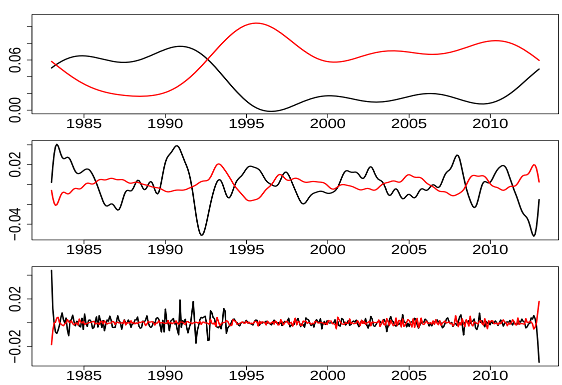

Figure 27: Filtered time series for Sweden.

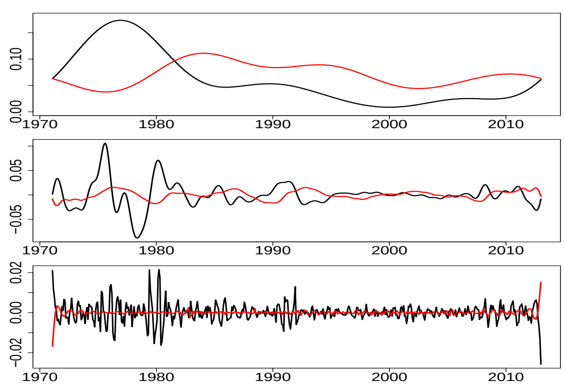

Figure 28: Filtered time series for UK.

B Estimation for Paramters, Standard Deviation of Shocks, and the Correlation of Structural Shocks (without Survey Data)

Below are Bayesian estimation results for paramters, standard deviations of shocks, and the correlations of structural shocks (without Survey Data). Note that some prior specifications are different from others. If so, we mark the corresponding entries red.

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
				Paramter Estimation			
α	norm	0.800	0.020	0.8288	0.0178	0.8033	0.8577
ζ	gamma	0.500	0.200	0.1097	0.0384	0.0520	0.1677
μ_y	gamma	3.060	0.300	2.9515	0.1805	2.6512	3.2753
μ_π	gamma	3.060	0.300	3.1119	0.2386	2.7736	3.4632
ρ_1	norm	1.350	0.020	1.3653	0.0178	1.3365	1.3924
ρ_2	norm	-0.500	0.020	-0.4852	0.0172	-0.5098	-0.4581
η_0	norm	-0.400	0.200	-0.4498	0.1626	-0.6960	-0.1590
η_1	norm	0.000	0.200	-0.3625	0.1305	-0.5566	-0.1636
				Estimation of the Standard Deviation of Structural Shocks			
σ_g	inverse-gamma	0.002	0.001	0.0014	0.0003	0.0010	0.0018
σ_n	inverse-gamma	0.007	0.001	0.0089	0.0004	0.0083	0.0097
σ_π	inverse-gamma	0.008	0.001	0.0074	0.0004	0.0069	0.0079
σ_u	inverse-gamma	0.002	0.001	0.0018	0.0001	0.0016	0.0020
				Estimation of the Correlation of Structual Shocks			
ρ_{ng}	norm	0.000	0.250	0.3316	0.1269	0.1423	0.5206
ρ_{nu}	norm	0.000	0.250	-0.2383	0.0845	-0.3676	-0.1209
$\rho_{n\pi}$	norm	0.000	0.250	-0.1227	0.0757	-0.2363	0.0003
ρ_{gu}	norm	0.000	0.250	0.1484	0.1616	-0.1163	0.3744
$\rho_{g\pi}$	norm	0.000	0.250	0.0495	0.1704	-0.2533	0.3231
$\rho_{u\pi}$	norm	0.000	0.250	0.0197	0.0783	-0.1076	0.1614

Table 4: Results from Metropolis Hastings for Austria (1960:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8282	0.0189	0.7977	0.8593
ζ	gamma	0.500	0.200	0.3233	0.0957	0.1749	0.4998
μ_y	gamma	3.060	0.300	2.4387	0.1536	2.1949	2.7244
μ_π	gamma	3.060	0.300	3.2112	0.2693	2.7456	3.7176
ρ_1	norm	1.350	0.020	1.3683	0.0174	1.3396	1.3915
ρ_2	norm	-0.500	0.020	-0.4823	0.0165	-0.5118	-0.4518
η_0	norm	-0.400	0.200	-0.5222	0.1719	-0.8466	-0.2348
η_1	norm	0.000	0.200	-0.1970	0.1480	-0.4781	0.0575
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0018	0.0005	0.0010	0.0025
σ_n	inverse-gamma	0.007	0.001	0.0070	0.0004	0.0062	0.0077
σ_π	inverse-gamma	0.008	0.001	0.0054	0.0003	0.0048	0.0059
σ_u	inverse-gamma	0.002	0.001	0.0036	0.0002	0.0033	0.0039
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.1277	0.1248	-0.1070	0.3656
ρ_{nu}	norm	0.000	0.250	-0.2861	0.0762	-0.4309	-0.1711
$\rho_{n\pi}$	norm	0.000	0.250	0.0059	0.1168	-0.1742	0.1939
ρ_{gu}	norm	0.000	0.250	0.2938	0.1252	0.0638	0.5072
$\rho_{g\pi}$	norm	0.000	0.250	-0.2868	0.2170	-0.6107	0.0731
$\rho_{u\pi}$	norm	0.000	0.250	-0.1009	0.1050	-0.2913	0.0784

Table 5: Results from Metropolis Hastings for Belgium (1970:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8020	0.0198	0.7679	0.8377
ζ	gamma	0.500	0.200	0.3651	0.1028	0.1783	0.5245
μ_y	gamma	3.060	0.300	3.2498	0.3145	2.8246	3.7301
μ_π	gamma	3.060	0.300	3.1154	0.2989	2.6317	3.5352
ρ_1	norm	1.350	0.020	1.3505	0.0205	1.3191	1.3848
ρ_2	norm	-0.500	0.020	-0.5039	0.0203	-0.5337	-0.4781
η_0	norm	-0.400	0.200	-0.4705	0.2042	-0.7795	-0.1302
η_1	norm	0.000	0.200	-0.1131	0.2181	-0.4256	0.2290
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0014	0.0004	0.0006	0.0024
σ_n	inverse-gamma	0.007	0.01	0.0273	0.0025	0.0230	0.0312
σ_π	inverse-gamma	0.008	0.01	0.0150	0.0014	0.0127	0.0173
σ_u	inverse-gamma	0.002	0.01	0.0062	0.0006	0.0049	0.0073
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0608	0.2456	-0.3224	0.3497
ρ_{nu}	norm	0.000	0.250	-0.2053	0.1127	-0.4044	-0.0196
$\rho_{n\pi}$	norm	0.000	0.250	0.0951	0.1239	-0.0756	0.3035
ρ_{gu}	norm	0.000	0.250	-0.0905	0.2451	-0.5153	0.2418
$\rho_{g\pi}$	norm	0.000	0.250	-0.0807	0.2555	-0.4389	0.3181
$\rho_{u\pi}$	norm	0.000	0.250	-0.0116	0.1260	-0.1925	0.1923

Table 6: Results from Metropolis Hastings for Bulgaria (2000:Q2 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8078	0.0192	0.7731	0.8410
ζ	gamma	0.500	0.200	0.2124	0.0738	0.1090	0.3361
μ_y	gamma	3.060	0.300	3.2117	0.2975	2.6743	3.6669
μ_π	gamma	3.060	0.300	2.9974	0.2697	2.5626	3.4181
ρ_1	norm	1.350	0.020	1.3406	0.0192	1.3112	1.3692
ρ_2	norm	-0.500	0.020	-0.5092	0.0191	-0.5388	-0.4780
η_0	norm	-0.400	0.200	-0.3914	0.1982	-0.6922	0.0211
η_1	norm	0.000	0.200	-0.0062	0.1996	-0.3470	0.2839
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0014	0.0003	0.0009	0.0019
σ_n	inverse-gamma	0.007	0.001	0.0170	0.0013	0.0148	0.0194
σ_π	inverse-gamma	0.008	0.001	0.0086	0.0007	0.0074	0.0097
σ_u	inverse-gamma	0.002	0.001	0.0062	0.0005	0.0052	0.0072
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0298	0.2219	-0.3086	0.3877
ρ_{nu}	norm	0.000	0.250	-0.1950	0.0991	-0.3592	-0.052
$\rho_{n\pi}$	norm	0.000	0.250	-0.0198	0.1146	-0.2041	0.1576
ρ_{gu}	norm	0.000	0.250	-0.0104	0.2356	-0.4300	0.3634
$\rho_{g\pi}$	norm	0.000	0.250	-0.0583	0.2554	-0.4559	0.3236
$\rho_{u\pi}$	norm	0.000	0.250	-0.0347	0.1207	-0.2054	0.1767

Table 7: Results from Metropolis Hastings for Croatia (2000:Q3 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8109	0.0198	0.7818	0.8430
ζ	gamma	0.500	0.200	0.1000	0.0346	0.0453	0.1581
μ_y	gamma	3.060	0.300	3.2505	0.2942	2.6994	3.6837
μ_π	gamma	3.060	0.300	2.9459	0.2852	2.4953	3.3617
ρ_1	norm	1.350	0.020	1.3497	0.0196	1.3219	1.3872
ρ_2	norm	-0.500	0.020	-0.5067	0.0196	-0.5365	-0.4780
η_0	norm	-0.400	0.200	-0.5092	0.2026	-0.8082	-0.2048
η_1	norm	0.000	0.200	-0.1726	0.2105	-0.4692	0.1543
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0021	0.0007	0.0010	0.0031
σ_n	inverse-gamma	0.007	0.001	0.0136	0.0011	0.0119	0.0154
σ_π	inverse-gamma	0.008	0.001	0.0174	0.0013	0.0151	0.0198
σ_u	inverse-gamma	0.002	0.001	0.0048	0.0006	0.0038	0.0057
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2633	0.2109	-0.0479	0.5728
ρ_{nu}	norm	0.000	0.250	-0.2836	0.1123	-0.4554	-0.1030
$\rho_{n\pi}$	norm	0.000	0.250	-0.2862	0.1123	-0.4416	-0.1082
ρ_{gu}	norm	0.000	0.250	-0.0103	0.2363	-0.3540	0.3690
$\rho_{g\pi}$	norm	0.000	0.250	-0.0098	0.2593	-0.4099	0.4256
$\rho_{u\pi}$	norm	0.000	0.250	-0.0183	0.1139	-0.1944	0.1583

Table 8: Results from Metropolis Hastings for Cyprus (2000:Q2 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8441	0.0188	0.8092	0.8702
ζ	gamma	0.500	0.200	0.1757	0.0582	0.0716	0.2777
μ_y	gamma	3.060	0.300	2.8716	0.2241	2.5142	3.2251
μ_π	gamma	3.060	0.300	3.1372	0.2802	2.6100	3.6174
ρ_1	norm	1.350	0.020	1.3623	0.0181	1.3356	1.3919
ρ_2	norm	-0.500	0.020	-0.5023	0.0175	-0.5319	-0.4762
η_0	norm	-0.400	0.200	-0.5697	0.1676	-0.8203	-0.2940
η_1	norm	0.000	0.200	-0.4131	0.1303	-0.5912	-0.1924
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0027	0.0007	0.0017	0.0038
σ_n	inverse-gamma	0.007	0.001	0.0083	0.0006	0.0073	0.0092
σ_π	inverse-gamma	0.008	0.001	0.0099	0.0007	0.0087	0.0112
σ_u	inverse-gamma	0.002	0.001	0.0018	0.0002	0.0013	0.0022
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0314	0.1434	-0.1820	0.2815
ρ_{nu}	norm	0.000	0.250	-0.2117	0.1402	-0.4123	0.0147
$\rho_{n\pi}$	norm	0.000	0.250	-0.0579	0.1119	-0.1994	0.1062
ρ_{gu}	norm	0.000	0.250	0.0755	0.2409	-0.3215	0.4511
$\rho_{g\pi}$	norm	0.000	0.250	-0.0455	0.1639	-0.2934	0.2078
$\rho_{u\pi}$	norm	0.000	0.250	0.3518	0.1249	0.1537	0.5745

Table 9: Results from Metropolis Hastings for Czech Republic (1995:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8643	0.0160	0.8310	0.8914
ζ	gamma	0.500	0.200	0.2995	0.0797	0.1200	0.4489
μ_y	gamma	3.060	0.300	2.5170	0.2049	2.2050	2.8311
μ_π	gamma	3.060	0.300	3.4417	0.2895	2.9561	3.9856
ρ_1	norm	1.350	0.020	1.3642	0.0233	1.3315	1.4019
ρ_2	norm	-0.500	0.020	-0.4912	0.0213	-0.5346	-0.4542
η_0	norm	-0.400	0.200	-0.8388	0.1355	-1.0935	-0.5441
η_1	norm	0.000	0.200	-0.2320	0.0989	-0.4831	0.0231
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0034	0.0007	0.0019	0.0047
σ_n	inverse-gamma	0.007	0.001	0.0112	0.0007	0.0102	0.0123
σ_π	inverse-gamma	0.008	0.001	0.0083	0.0005	0.0073	0.0091
σ_u	inverse-gamma	0.002	0.001	0.0031	0.0007	0.0023	0.0039
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.0445	0.1197	-0.3201	0.2761
ρ_{nu}	norm	0.000	0.250	-0.0970	0.1122	-0.2611	0.0789
$\rho_{n\pi}$	norm	0.000	0.250	0.0970	0.0712	-0.0325	0.2100
ρ_{gu}	norm	0.000	0.250	0.6037	0.0703	0.2715	0.9268
$\rho_{g\pi}$	norm	0.000	0.250	-0.1683	0.1155	-0.4213	0.0763
$\rho_{u\pi}$	norm	0.000	0.250	-0.0451	0.0970	-0.2453	0.1311

Table 10: Results from Metropolis Hastings for Denmark (1970:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8132	0.0205	0.7763	0.8596
ζ	gamma	0.500	0.200	0.3173	0.1064	0.1737	0.4950
μ_y	gamma	3.060	0.300	3.1869	0.2877	2.7019	3.6719
μ_π	gamma	3.060	0.300	3.1556	0.2933	2.7608	3.6244
ρ_1	norm	1.350	0.020	1.3478	0.0188	1.3137	1.3794
ρ_2	norm	-0.500	0.020	-0.5056	0.0191	-0.5344	-0.4718
η_0	norm	-0.400	0.200	-0.4060	0.2003	-0.8048	-0.0915
η_1	norm	0.000	0.200	-0.2134	0.2179	-0.6239	0.1494
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0022	0.0007	0.0010	0.0035
σ_n	inverse-gamma	0.007	0.001	0.0176	0.0013	0.0152	0.0198
σ_π	inverse-gamma	0.008	0.001	0.0073	0.0006	0.0063	0.0081
σ_u	inverse-gamma	0.002	0.001	0.0081	0.0007	0.0069	0.0098
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2343	0.1716	-0.0347	0.4871
ρ_{nu}	norm	0.000	0.250	-0.3610	0.0950	-0.5396	-0.1978
$\rho_{n\pi}$	norm	0.000	0.250	-0.0814	0.1381	-0.2850	0.1302
ρ_{gu}	norm	0.000	0.250	-0.0498	0.1708	-0.3472	0.1750
$\rho_{g\pi}$	norm	0.000	0.250	0.0533	0.2393	-0.3289	0.4658
$\rho_{u\pi}$	norm	0.000	0.250	0.0096	0.1662	-0.2658	0.2661

Table 11: Results from Metropolis Hastings for Estonia (1997:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.9150	0.0235	0.9035	0.9272
ζ	gamma	0.500	0.200	0.5732	0.0775	0.4646	0.7035
μ_y	gamma	3.060	0.300	2.9186	0.2298	2.6102	3.2739
μ_π	gamma	3.060	0.300	3.2782	0.3042	2.9002	3.6213
ρ_1	norm	1.350	0.020	1.4042	0.0171	1.3819	1.4328
ρ_2	norm	-0.500	0.020	-0.4710	0.0159	-0.4935	-0.4487
η_0	norm	-0.400	0.200	-0.8045	0.2056	-1.0692	-0.5662
η_1	norm	0.000	0.200	-0.6122	0.2162	-0.7899	-0.3676
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0025	0.0005	0.0022	0.0030
σ_n	inverse-gamma	0.007	0.01	0.0135	0.0007	0.0125	0.0146
σ_π	inverse-gamma	0.008	0.01	0.0072	0.0005	0.0067	0.0079
σ_u	inverse-gamma	0.002	0.01	0.0022	0.0002	0.0014	0.0034
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2275	0.1468	0.0866	0.4049
ρ_{nu}	norm	0.000	0.250	-0.1197	0.0644	-0.2576	0.0573
$\rho_{n\pi}$	norm	0.000	0.250	-0.0213	0.0924	-0.1433	0.0901
ρ_{gu}	norm	0.000	0.250	0.1810	0.1108	-0.1082	0.4382
$\rho_{g\pi}$	norm	0.000	0.250	-0.1400	0.2655	-0.2951	0.0190
$\rho_{u\pi}$	norm	0.000	0.250	-0.1520	0.1198	-0.3234	-0.0039

Table 12: Results from Metropolis Hastings for Finland (1964:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
	Paramter Estimation						
α	norm	0.800	0.020	0.8292	0.0184	0.7982	0.8589
ζ	gamma	0.500	0.200	0.2610	0.0876	0.1106	0.3978
μ_y	gamma	3.060	0.300	2.4058	0.1354	2.1887	2.6444
μ_π	gamma	3.060	0.300	3.1931	0.2934	2.7074	3.5754
ρ_1	norm	1.350	0.020	1.3877	0.0295	1.3624	1.4113
ρ_2	norm	-0.500	0.020	-0.4573	0.0157	-0.4793	-0.4304
η_0	norm	-0.400	0.200	-0.4642	0.2071	-0.8441	-0.1994
η_1	norm	0.000	0.200	-0.2328	0.1889	-0.5322	0.0642
	Estimation of the Standard Deviation of Structual Shocks						
σ_g	inverse-gamma	0.002	0.001	0.0013	0.0008	0.0008	0.0018
σ_n	inverse-gamma	0.007	0.001	0.0058	0.0003	0.0054	0.0062
σ_π	inverse-gamma	0.008	0.001	0.0050	0.0004	0.0045	0.0055
σ_u	inverse-gamma	0.002	0.001	0.0031	0.0002	0.0028	0.0034
	Estimation of the Correlation of Structual Shocks						
ρ_{ng}	norm	0.000	0.250	0.1063	0.1417	-0.0532	0.2717
ρ_{nu}	norm	0.000	0.250	-0.2505	0.0795	-0.3680	-0.1410
$\rho_{n\pi}$	norm	0.000	0.250	0.1191	0.1651	-0.0870	0.3149
ρ_{gu}	norm	0.000	0.250	0.3543	0.1694	0.1585	0.5063
$\rho_{g\pi}$	norm	0.000	0.250	-0.5457	0.2857	-0.9608	-0.1892
$\rho_{u\pi}$	norm	0.000	0.250	-0.2687	0.1038	-0.4144	-0.0980

Table 13: Results from Metropolis Hastings for France (1969:Q3 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
	Paramter Estimation						
α	norm	0.800	0.020	0.8390	0.0189	0.8063	0.8734
ζ	gamma	0.500	0.200	0.2808	0.0911	0.1268	0.4326
μ_y	gamma	3.060	0.300	2.4162	0.1933	2.1031	2.7525
μ_π	gamma	3.060	0.300	2.8298	0.2342	2.4281	3.2136
ρ_1	norm	1.350	0.020	1.3525	0.0174	1.3233	1.3868
ρ_2	norm	-0.500	0.020	-0.4972	0.0151	-0.5240	-0.4680
η_0	norm	-0.400	0.200	-0.6033	0.1732	-0.9412	-0.2731
η_1	norm	0.000	0.200	-0.3347	0.1405	-0.5848	-0.0817
	Estimation of the Standard Deviation of Structual Shocks						
σ_g	inverse-gamma	0.002	0.001	0.0017	0.0004	0.0010	0.0023
σ_n	inverse-gamma	0.007	0.001	0.0078	0.0005	0.0070	0.0087
σ_π	inverse-gamma	0.008	0.001	0.0057	0.0004	0.0051	0.0063
σ_u	inverse-gamma	0.002	0.001	0.0024	0.0003	0.0018	0.0028
	Estimation of the Correlation of Structual Shocks						
ρ_{ng}	norm	0.000	0.250	0.3162	0.1564	0.0572	0.5726
ρ_{nu}	norm	0.000	0.250	-0.0829	0.1241	-0.2946	0.0915
$\rho_{n\pi}$	norm	0.000	0.250	0.0253	0.1218	-0.1953	0.2557
ρ_{gu}	norm	0.000	0.250	0.1100	0.1666	-0.1877	0.4258
$\rho_{g\pi}$	norm	0.000	0.250	-0.3550	0.1718	-0.7131	-0.0601
$\rho_{u\pi}$	norm	0.000	0.250	-0.0123	0.1755	-0.2644	0.2391

Table 14: Results from Metropolis Hastings for France (1991:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8039	0.0196	0.7740	0.8321
ζ	gamma	0.500	0.200	0.1076	0.0397	0.0458	0.1847
μ_y	gamma	3.060	0.300	3.0117	0.2928	2.5214	3.4921
μ_π	gamma	3.060	0.300	3.0078	0.2829	2.5678	3.5152
ρ_1	norm	1.350	0.020	1.3480	0.0197	1.3159	1.3802
ρ_2	norm	-0.500	0.020	-0.5041	0.0197	-0.5312	-0.4741
η_0	norm	-0.400	0.200	-0.4103	0.2020	-0.7601	-0.1078
η_1	norm	0.000	0.200	-0.0344	0.2055	-0.3580	0.2807
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0012	0.0003	0.0005	0.0019
σ_n	inverse-gamma	0.007	0.01	0.0504	0.0043	0.0433	0.0578
σ_π	inverse-gamma	0.008	0.01	0.0153	0.0014	0.0129	0.0176
σ_u	inverse-gamma	0.002	0.01	0.0070	0.0006	0.0059	0.0082
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.0166	0.2472	-0.4226	0.3806
ρ_{nu}	norm	0.000	0.250	-0.4267	0.0993	-0.6046	-0.2857
$\rho_{n\pi}$	norm	0.000	0.250	-0.0468	0.1114	-0.2437	0.1625
ρ_{gu}	norm	0.000	0.250	-0.0057	0.2475	-0.3721	0.3671
$\rho_{g\pi}$	norm	0.000	0.250	-0.1094	0.2604	-0.5466	0.3180
$\rho_{u\pi}$	norm	0.000	0.250	-0.0510	0.1173	-0.2364	0.1468

Table 15: Results from Metropolis Hastings for Greece (1998:Q3 – 2013:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8037	0.0191	0.7701	0.8363
ζ	gamma	0.500	0.200	0.5166	0.1451	0.3113	0.7647
μ_y	gamma	3.060	0.300	2.6731	0.2213	2.3006	3.0610
μ_π	gamma	3.060	0.300	3.1940	0.3096	2.6697	3.6538
ρ_1	norm	1.350	0.020	1.3632	0.0208	1.3302	1.3930
ρ_2	norm	-0.500	0.020	-0.4924	0.0209	-0.5277	-0.4540
η_0	norm	-0.400	0.200	-0.3001	0.1984	-0.6677	0.0680
η_1	norm	0.000	0.200	-0.0294	0.2026	-0.4021	0.2986
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0016	0.0004	0.0009	0.0022
σ_n	inverse-gamma	0.007	0.001	0.0088	0.0006	0.0077	0.0099
σ_π	inverse-gamma	0.008	0.001	0.0113	0.0011	0.0093	0.0130
σ_u	inverse-gamma	0.002	0.001	0.0031	0.0003	0.0026	0.0036
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.0426	0.1589	-0.2907	0.2333
ρ_{nu}	norm	0.000	0.250	-0.2138	0.0986	-0.3936	-0.0351
$\rho_{n\pi}$	norm	0.000	0.250	-0.0378	0.1303	-0.2276	0.1822
ρ_{gu}	norm	0.000	0.250	-0.0388	0.1902	-0.3888	0.2916
$\rho_{g\pi}$	norm	0.000	0.250	0.1066	0.2253	-0.2676	0.4796
$\rho_{u\pi}$	norm	0.000	0.250	-0.0375	0.1333	-0.2423	0.1479

Table 16: Results from Metropolis Hastings for Hungary (1995:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8185	0.0189	0.7916	0.8466
ζ	gamma	0.500	0.200	0.2314	0.0768	0.0976	0.3528
μ_y	gamma	3.060	0.300	3.4096	0.2790	2.9516	3.9062
μ_π	gamma	3.060	0.300	2.9442	0.2550	2.4980	3.3355
ρ_1	norm	1.350	0.020	1.3521	0.0185	1.3184	1.3827
ρ_2	norm	-0.500	0.020	-0.5001	0.0179	-0.5311	-0.4693
η_0	norm	-0.400	0.200	-0.5913	0.1879	-0.8804	-0.2786
η_1	norm	0.000	0.200	-0.2388	0.1720	-0.5286	0.0313
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0019	0.0005	0.0011	0.0026
σ_n	inverse-gamma	0.007	0.001	0.0147	0.0009	0.0132	0.0162
σ_π	inverse-gamma	0.008	0.001	0.0063	0.0004	0.0057	0.0070
σ_u	inverse-gamma	0.002	0.001	0.0044	0.0003	0.0039	0.0050
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2596	0.1593	-0.0084	0.5192
ρ_{nu}	norm	0.000	0.250	-0.3279	0.0757	-0.4536	-0.2190
$\rho_{n\pi}$	norm	0.000	0.250	-0.0326	0.1161	-0.2068	0.1554
ρ_{gu}	norm	0.000	0.250	0.1585	0.1692	-0.1410	0.4578
$\rho_{g\pi}$	norm	0.000	0.250	0.0487	0.2273	-0.3027	0.4054
$\rho_{u\pi}$	norm	0.000	0.250	-0.2185	0.1508	-0.4189	0.0134

Table 17: Results from Metropolis Hastings for Ireland (1983:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8188	0.0188	0.7913	0.8514
ζ	gamma	0.500	0.200	0.9659	0.0032	0.9325	0.9955
μ_y	gamma	3.060	0.300	2.1789	0.1704	1.8722	2.4403
μ_π	gamma	3.060	0.300	3.0820	0.2996	2.6131	3.5206
ρ_1	norm	1.350	0.020	1.3395	0.0179	1.3131	1.3700
ρ_2	norm	-0.500	0.020	-0.5192	0.0185	-0.5479	-0.4907
η_0	norm	-0.400	0.200	-0.3222	0.1951	-0.6742	-0.0024
η_1	norm	0.000	0.200	-0.1740	0.1654	-0.4461	0.0933
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0013	0.0003	0.0009	0.0017
σ_n	inverse-gamma	0.007	0.001	0.0076	0.0004	0.0069	0.0083
σ_π	inverse-gamma	0.008	0.001	0.0057	0.0003	0.0052	0.0062
σ_u	inverse-gamma	0.002	0.001	0.0025	0.0002	0.0022	0.0027
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.1263	0.1141	-0.3944	0.1272
ρ_{nu}	norm	0.000	0.250	-0.2277	0.0783	-0.3631	-0.1001
$\rho_{n\pi}$	norm	0.000	0.250	0.1872	0.0973	0.0170	0.3415
ρ_{gu}	norm	0.000	0.250	-0.0717	0.1642	-0.4474	0.2686
$\rho_{g\pi}$	norm	0.000	0.250	-0.7461	0.0327	-0.9147	-0.6160
$\rho_{u\pi}$	norm	0.000	0.250	-0.0447	0.1501	-0.2632	0.1994

Table 18: Results from Metropolis Hastings for Italy (1979:Q4 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.020	0.8504	0.0180	0.8133	0.8812
ζ	gamma	0.500	0.200	0.2262	0.0739	0.1047	0.3434
μ_y	gamma	3.060	0.300	3.1813	0.3101	2.7154	3.7550
μ_π	gamma	3.060	0.300	3.0966	0.2885	2.6623	3.6286
ρ_1	norm	1.350	0.020	1.3497	0.0179	1.3217	1.3800
ρ_2	norm	-0.500	0.020	-0.5079	0.0170	-0.5367	-0.4791
η_0	norm	-0.400	0.200	-0.6931	0.1633	-0.9646	-0.4266
η_1	norm	0.000	0.200	-0.5085	0.1448	-0.7583	-0.2181
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.1	0.0052	0.0012	0.0033	0.0071
σ_n	inverse-gamma	0.007	0.1	0.0381	0.0031	0.0317	0.0440
σ_π	inverse-gamma	0.008	0.1	0.0115	0.0012	0.0094	0.0135
σ_u	inverse-gamma	0.002	0.1	0.0054	0.0008	0.0038	0.0071
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.250	0.4237	0.1376	0.1726	0.6972
ρ_{nu}	norm	0.000	0.250	-0.0950	0.1404	-0.3235	0.1468
$\rho_{n\pi}$	norm	0.000	0.250	-0.1272	0.1265	-0.3481	0.0948
ρ_{gu}	norm	0.000	0.250	0.0550	0.2206	-0.2492	0.4112
$\rho_{g\pi}$	norm	0.000	0.250	-0.0970	0.1725	-0.3839	0.1707
$\rho_{u\pi}$	norm	0.000	0.250	0.1408	0.1461	-0.0913	0.3486

Table 19: Results from Metropolis Hastings for Latvia (1998:Q2 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.020	0.8029	0.0200	0.7692	0.8350
ζ	gamma	0.500	0.200	0.2416	0.0926	0.0973	0.3671
μ_y	gamma	3.060	0.300	3.1738	0.3069	2.6533	3.6019
μ_π	gamma	3.060	0.300	2.9779	0.2800	2.5327	3.4862
ρ_1	norm	1.350	0.020	1.3503	0.0197	1.3218	1.3808
ρ_2	norm	-0.500	0.020	-0.4977	0.0212	-0.5293	-0.4667
η_0	norm	-0.400	0.200	-0.4776	0.2028	-0.7853	-0.1522
η_1	norm	0.000	0.200	-0.0922	0.2071	-0.4214	0.2427
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.1	0.0017	0.0007	0.0006	0.0030
σ_n	inverse-gamma	0.007	0.1	0.0395	0.0033	0.0330	0.0457
σ_π	inverse-gamma	0.008	0.1	0.0099	0.0010	0.0080	0.0116
σ_u	inverse-gamma	0.002	0.1	0.0091	0.0008	0.0078	0.0104
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.250	0.1732	0.2038	-0.1431	0.5019
ρ_{nu}	norm	0.000	0.250	-0.2550	0.1068	-0.4213	-0.0957
$\rho_{n\pi}$	norm	0.000	0.250	-0.1981	0.1256	-0.3790	-0.0066
ρ_{gu}	norm	0.000	0.250	-0.0016	0.1887	-0.2814	0.3393
$\rho_{g\pi}$	norm	0.000	0.250	0.0904	0.2410	-0.2637	0.5112
$\rho_{u\pi}$	norm	0.000	0.250	-0.0159	0.1399	-0.2531	0.1957

Table 20: Results from Metropolis Hastings for Lithuania (1998:Q2 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8293	0.0260	0.7966	0.8642
ζ	gamma	0.500	0.200	0.2474	0.0750	0.1004	0.3671
μ_y	gamma	3.060	0.300	3.3297	0.2825	2.8390	3.7645
μ_π	gamma	3.060	0.300	2.7186	0.2074	2.4122	3.0482
ρ_1	norm	1.350	0.020	1.3495	0.0177	1.3199	1.3781
ρ_2	norm	-0.500	0.020	-0.5059	0.0189	-0.5320	-0.4774
η_0	norm	-0.400	0.200	-0.5068	0.0488	-0.6802	-0.3375
η_1	norm	0.000	0.200	-0.3374	0.0356	-0.5239	-0.1656
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0011	0.0002	0.0007	0.0015
σ_n	inverse-gamma	0.007	0.01	0.0163	0.0010	0.0147	0.0183
σ_π	inverse-gamma	0.008	0.01	0.0057	0.0004	0.0050	0.0063
σ_u	inverse-gamma	0.002	0.01	0.0013	0.0001	0.0010	0.0015
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.1181	0.1451	-0.0957	0.3613
ρ_{nu}	norm	0.000	0.250	-0.1676	0.1013	-0.3356	-0.0179
$\rho_{n\pi}$	norm	0.000	0.250	-0.0807	0.0878	-0.2182	0.0698
ρ_{gu}	norm	0.000	0.250	-0.1509	0.1946	-0.4215	0.2297
$\rho_{g\pi}$	norm	0.000	0.250	-0.1997	0.1698	-0.4583	0.0728
$\rho_{u\pi}$	norm	0.000	0.250	0.0520	0.1215	-0.1470	0.2475

Table 21: Results from Metropolis Hastings for Luxembourg (1983:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.7982	0.0199	0.7688	0.8291
ζ	gamma	0.500	0.200	0.2427	0.0793	0.1257	0.3808
μ_y	gamma	3.060	0.300	3.1255	0.2924	2.6614	3.5609
μ_π	gamma	3.060	0.300	3.0274	0.2929	2.5498	3.4372
ρ_1	norm	1.350	0.020	1.3469	0.0198	1.3105	1.3862
ρ_2	norm	-0.500	0.020	-0.4991	0.0198	-0.5307	-0.4685
η_0	norm	-0.400	0.200	-0.3753	0.1977	-0.7034	-0.1014
η_1	norm	0.000	0.200	0.0131	0.2010	-0.3148	0.3597
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0011	0.0003	0.0005	0.0016
σ_n	inverse-gamma	0.007	0.001	0.0171	0.0016	0.0142	0.0193
σ_π	inverse-gamma	0.008	0.001	0.0299	0.0027	0.0260	0.0350
σ_u	inverse-gamma	0.002	0.001	0.0030	0.0003	0.0025	0.0036
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0275	0.2485	-0.3966	0.4213
ρ_{nu}	norm	0.000	0.250	-0.0051	0.1180	-0.1909	0.2032
$\rho_{n\pi}$	norm	0.000	0.250	0.0237	0.1153	-0.1532	0.1917
ρ_{gu}	norm	0.000	0.250	-0.0039	0.2510	-0.3910	0.3948
$\rho_{g\pi}$	norm	0.000	0.250	-0.0138	0.2508	-0.4317	0.3747
$\rho_{u\pi}$	norm	0.000	0.250	0.0021	0.1172	-0.2050	0.1864

Table 22: Results from Metropolis Hastings for Malta (2000:Q3 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8460	0.0190	0.8139	0.8805
ζ	gamma	0.500	0.200	0.1474	0.0512	0.0525	0.2436
μ_y	gamma	3.060	0.300	2.6609	0.1884	2.2909	2.9559
μ_π	gamma	3.060	0.300	3.1678	0.2550	2.8128	3.5640
ρ_1	norm	1.350	0.020	1.3778	0.0144	1.3502	1.4055
ρ_2	norm	-0.500	0.020	-0.4725	0.0119	-0.5002	-0.4449
η_0	norm	-0.400	0.200	-0.5974	0.1736	-0.8702	-0.3250
η_1	norm	0.000	0.200	-0.3641	0.1420	-0.5933	-0.1411
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0019	0.0004	0.0012	0.0025
σ_n	inverse-gamma	0.007	0.001	0.0104	0.0005	0.0095	0.0113
σ_π	inverse-gamma	0.008	0.001	0.0062	0.0004	0.0055	0.0067
σ_u	inverse-gamma	0.002	0.001	0.0027	0.0002	0.0024	0.0031
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.3615	0.1096	0.1595	0.5520
ρ_{nu}	norm	0.000	0.250	-0.1201	0.0852	-0.2547	0.0280
$\rho_{n\pi}$	norm	0.000	0.250	-0.0089	0.0830	-0.1324	0.1240
ρ_{gu}	norm	0.000	0.250	0.2942	0.1102	0.1164	0.5182
$\rho_{g\pi}$	norm	0.000	0.250	-0.4035	0.1599	-0.6523	-0.1548
$\rho_{u\pi}$	norm	0.000	0.250	0.0495	0.1180	-0.1089	0.2132

Table 23: Results from Metropolis Hastings for Netherlands (1970:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.7986	0.0189	0.7674	0.8269
ζ	gamma	0.500	0.200	0.3185	0.1052	0.1291	0.4933
μ_y	gamma	3.060	0.300	3.4327	0.2588	3.0344	3.8500
μ_π	gamma	3.060	0.300	3.1693	0.3006	2.6469	3.6634
ρ_1	norm	1.350	0.020	1.3629	0.0189	1.3348	1.3929
ρ_2	norm	-0.500	0.020	-0.4867	0.0185	-0.5146	-0.4587
η_0	norm	-0.400	0.200	-0.3869	0.1958	-0.7481	-0.0568
η_1	norm	0.000	0.200	-0.0583	0.1965	-0.3537	0.2519
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0019	0.0005	0.0010	0.0026
σ_n	inverse-gamma	0.007	0.001	0.0092	0.0007	0.0080	0.0103
σ_π	inverse-gamma	0.008	0.001	0.0093	0.0008	0.0080	0.0107
σ_u	inverse-gamma	0.002	0.001	0.0054	0.0004	0.0047	0.0062
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2668	0.2208	-0.0626	0.6023
ρ_{nu}	norm	0.000	0.250	-0.2064	0.1002	-0.3633	-0.0508
$\rho_{n\pi}$	norm	0.000	0.250	-0.0237	0.1202	-0.2285	0.1820
ρ_{gu}	norm	0.000	0.250	0.0209	0.1623	-0.2741	0.3045
$\rho_{g\pi}$	norm	0.000	0.250	0.2264	0.2301	-0.0940	0.5574
$\rho_{u\pi}$	norm	0.000	0.250	0.0298	0.1440	-0.2192	0.2117

Table 24: Results from Metropolis Hastings for Poland (1995:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8064	0.0193	0.7788	0.8372
ζ	gamma	0.500	0.200	0.2167	0.0681	0.0949	0.3368
μ_y	gamma	3.060	0.300	2.6856	0.2127	2.3728	3.0053
μ_π	gamma	3.060	0.300	3.1731	0.3067	2.7195	3.6819
ρ_1	norm	1.350	0.020	1.3881	0.0167	1.3622	1.4165
ρ_2	norm	-0.500	0.020	-0.4565	0.0160	-0.4831	-0.4286
η_0	norm	-0.400	0.200	-0.3545	0.1874	-0.6203	-0.0274
η_1	norm	0.000	0.200	-0.1468	0.1850	-0.4205	0.1229
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0016	0.0004	0.0010	0.0022
σ_n	inverse-gamma	0.007	0.001	0.0104	0.0006	0.0093	0.0113
σ_π	inverse-gamma	0.008	0.001	0.0091	0.0007	0.0076	0.0103
σ_u	inverse-gamma	0.002	0.001	0.0035	0.0002	0.0032	0.0039
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0253	0.1971	-0.3329	0.3035
ρ_{nu}	norm	0.000	0.250	-0.3922	0.0699	-0.5285	-0.2641
$\rho_{n\pi}$	norm	0.000	0.250	0.0126	0.1123	-0.1787	0.2000
ρ_{gu}	norm	0.000	0.250	-0.0276	0.1673	-0.3426	0.2631
$\rho_{g\pi}$	norm	0.000	0.250	0.1806	0.2274	-0.1526	0.5533
$\rho_{u\pi}$	norm	0.000	0.250	0.1086	0.1277	-0.0923	0.3013

Table 25: Results from Metropolis Hastings for Portugal (1983:Q4 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8049	0.0189	0.7681	0.8357
ζ	gamma	0.500	0.200	0.7016	0.1287	0.4484	0.9284
μ_y	gamma	3.060	0.300	3.2134	0.3076	2.7205	3.7746
μ_π	gamma	3.060	0.300	3.0800	0.3034	2.6465	3.5581
ρ_1	norm	1.350	0.020	1.3531	0.0200	1.3196	1.3880
ρ_2	norm	-0.500	0.020	-0.4983	0.0204	-0.5355	-0.4631
η_0	norm	-0.400	0.200	-0.5362	0.1481	-0.8144	-0.2224
η_1	norm	0.000	0.200	-0.0868	0.1051	-0.3294	0.1651
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0027	0.0009	0.0012	0.0044
σ_n	inverse-gamma	0.007	0.01	0.0452	0.0040	0.0380	0.0519
σ_π	inverse-gamma	0.008	0.01	0.0121	0.0012	0.0089	0.0142
σ_u	inverse-gamma	0.002	0.01	0.0022	0.0004	0.0007	0.0031
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.0187	0.1325	-0.2216	0.2731
ρ_{nu}	norm	0.000	0.250	-0.1311	0.2134	-0.3695	0.1219
$\rho_{n\pi}$	norm	0.000	0.250	0.0066	0.1254	-0.1814	0.1890
ρ_{gu}	norm	0.000	0.250	-0.1774	0.2511	-0.4748	0.1645
$\rho_{g\pi}$	norm	0.000	0.250	-0.1254	0.1470	-0.4389	0.1958
$\rho_{u\pi}$	norm	0.000	0.250	0.0446	0.2378	-0.2659	0.3317

Table 26: Results from Metropolis Hastings for Romania (2000:Q4 – 2014:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8048	0.0200	0.7707	0.8460
ζ	gamma	0.500	0.200	0.2803	0.0861	0.1434	0.4449
μ_y	gamma	3.060	0.300	3.1932	0.2751	2.7708	3.5758
μ_π	gamma	3.060	0.300	3.1774	0.3085	2.7144	3.6890
ρ_1	norm	1.350	0.020	1.3553	0.0202	1.3232	1.3876
ρ_2	norm	-0.500	0.020	-0.4933	0.0204	-0.5292	-0.4616
η_0	norm	-0.400	0.200	-0.4482	0.2032	-0.7124	-0.1165
η_1	norm	0.000	0.200	-0.2295	0.2450	-0.6019	0.1080
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0021	0.0007	0.0011	0.0032
σ_n	inverse-gamma	0.007	0.001	0.0143	0.0011	0.0121	0.0161
σ_π	inverse-gamma	0.008	0.001	0.0125	0.0011	0.0107	0.0148
σ_u	inverse-gamma	0.002	0.001	0.0055	0.0005	0.0046	0.0065
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.4529	0.2334	0.1839	0.7812
ρ_{nu}	norm	0.000	0.250	-0.1731	0.1002	-0.3618	-0.0124
$\rho_{n\pi}$	norm	0.000	0.250	-0.0602	0.1113	-0.1951	0.0861
ρ_{gu}	norm	0.000	0.250	0.0781	0.1849	-0.2599	0.4467
$\rho_{g\pi}$	norm	0.000	0.250	0.0104	0.2217	-0.3314	0.3684
$\rho_{u\pi}$	norm	0.000	0.250	0.1958	0.1251	-0.0126	0.3662

Table 27: Results from Metropolis Hastings for Slovakia (1993:Q3 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8092	0.0194	0.7816	0.8422
ζ	gamma	0.500	0.200	0.2103	0.0675	0.0997	0.3358
μ_y	gamma	3.060	0.300	2.8707	0.2461	2.5180	3.2827
μ_π	gamma	3.060	0.300	3.2215	0.3023	2.8460	3.6696
ρ_1	norm	1.350	0.020	1.3535	0.0189	1.3242	1.3839
ρ_2	norm	-0.500	0.020	-0.4969	0.0188	-0.5251	-0.4660
η_0	norm	-0.400	0.200	-0.3377	0.1948	-0.6396	-0.0464
η_1	norm	0.000	0.200	-0.1722	0.1920	-0.4697	0.1397
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0017	0.0005	0.0011	0.0024
σ_n	inverse-gamma	0.007	0.001	0.0105	0.0008	0.0093	0.0121
σ_π	inverse-gamma	0.008	0.001	0.0089	0.0007	0.0077	0.0100
σ_u	inverse-gamma	0.002	0.001	0.0035	0.0003	0.0030	0.0040
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.2432	0.1848	-0.0458	0.5576
ρ_{nu}	norm	0.000	0.250	-0.1870	0.1089	-0.3329	-0.0291
$\rho_{n\pi}$	norm	0.000	0.250	0.0188	0.1279	-0.1747	0.1943
ρ_{gu}	norm	0.000	0.250	0.0184	0.2072	-0.3005	0.3069
$\rho_{g\pi}$	norm	0.000	0.250	0.0566	0.2286	-0.2811	0.4259
$\rho_{u\pi}$	norm	0.000	0.250	-0.0420	0.1146	-0.2105	0.1152

Table 28: Results from Metropolis Hastings for Slovenia (1996:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8162	0.0197	0.7832	0.8488
ζ	gamma	0.500	0.200	0.0838	0.0319	0.0341	0.1288
μ_y	gamma	3.060	0.300	2.7541	0.1737	2.4964	3.0321
μ_π	gamma	3.060	0.300	3.3269	0.3096	2.8413	3.8490
ρ_1	norm	1.350	0.020	1.3854	0.0167	1.3554	1.4116
ρ_2	norm	-0.500	0.020	-0.4605	0.0160	-0.4874	-0.4339
η_0	norm	-0.400	0.200	-0.5725	0.2001	-0.8814	-0.2639
η_1	norm	0.000	0.200	-0.0955	0.1984	-0.3725	0.1956
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0015	0.0003	0.0010	0.0020
σ_n	inverse-gamma	0.007	0.001	0.0079	0.0004	0.0072	0.0086
σ_π	inverse-gamma	0.008	0.001	0.0081	0.0006	0.0072	0.0090
σ_u	inverse-gamma	0.002	0.001	0.0058	0.0003	0.0053	0.0063
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.0497	0.1788	-0.3115	0.2326
ρ_{nu}	norm	0.000	0.250	-0.5669	0.0548	-0.6563	-0.4667
$\rho_{n\pi}$	norm	0.000	0.250	0.0354	0.1113	-0.1499	0.2119
ρ_{gu}	norm	0.000	0.250	0.1322	0.1258	-0.0937	0.3591
$\rho_{g\pi}$	norm	0.000	0.250	0.2011	0.2345	-0.1532	0.5797
$\rho_{u\pi}$	norm	0.000	0.250	-0.0596	0.1254	-0.2349	0.1252

Table 29: Results from Metropolis Hastings for Spain (1978:Q1 – 2013:Q3)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8822	0.0237	0.8514	0.9237
ζ	gamma	0.500	0.200	0.2057	0.0606	0.0871	0.3154
μ_y	gamma	3.060	0.300	2.6228	0.2063	2.2347	2.9651
μ_π	gamma	3.060	0.300	3.2635	0.3047	2.7836	3.7829
ρ_1	norm	1.350	0.020	1.3984	0.0151	1.3718	1.4247
ρ_2	norm	-0.500	0.020	-0.4617	0.0108	-0.4867	-0.4375
η_0	norm	-0.400	0.200	-0.6768	0.1647	-0.9131	-0.4330
η_1	norm	0.000	0.200	-0.4771	0.1398	-0.6963	-0.2810
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.001	0.0021	0.0004	0.0014	0.0028
σ_n	inverse-gamma	0.007	0.001	0.0110	0.0006	0.0100	0.0119
σ_π	inverse-gamma	0.008	0.001	0.0085	0.0005	0.0076	0.0093
σ_u	inverse-gamma	0.002	0.001	0.0020	0.0002	0.0015	0.0024
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	0.1156	0.1252	-0.0634	0.3535
ρ_{nu}	norm	0.000	0.250	-0.1653	0.0958	-0.3041	-0.0099
$\rho_{n\pi}$	norm	0.000	0.250	0.0976	0.0732	-0.0314	0.2139
ρ_{gu}	norm	0.000	0.250	0.0772	0.1578	-0.1529	0.3296
$\rho_{g\pi}$	norm	0.000	0.250	-0.0788	0.1266	-0.2845	0.1536
$\rho_{u\pi}$	norm	0.000	0.250	0.1301	0.1067	-0.0672	0.3118

Table 30: Results from Metropolis Hastings for Sweden (1970:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.020	0.8780	0.0344	0.8414	0.9081
ζ	gamma	0.500	0.200	0.1353	0.0499	0.0504	0.2211
μ_y	gamma	3.060	0.300	2.4436	0.1840	2.2217	2.6114
μ_π	gamma	3.060	0.300	2.8779	0.2309	2.6148	3.0989
ρ_1	norm	1.350	0.020	1.3369	0.0193	1.3197	1.3577
ρ_2	norm	-0.500	0.020	-0.5243	0.0207	-0.5484	-0.5119
η_0	norm	-0.400	0.200	-0.7887	0.0573	-1.0353	-0.5854
η_1	norm	0.000	0.200	-0.1279	0.0249	-0.1967	-0.0755
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.01	0.0029	0.0010	0.0021	0.0038
σ_n	inverse-gamma	0.007	0.01	0.0062	0.0008	0.0053	0.0072
σ_π	inverse-gamma	0.008	0.01	0.0059	0.0006	0.0054	0.0064
σ_u	inverse-gamma	0.002	0.01	0.0019	0.0002	0.0017	0.0020
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.250	-0.2079	0.2197	-0.3854	0.0169
ρ_{nu}	norm	0.000	0.250	-0.2171	0.1104	-0.3343	-0.1048
$\rho_{n\pi}$	norm	0.000	0.250	0.0196	0.1503	-0.0468	0.1345
ρ_{gu}	norm	0.000	0.250	0.9741	0.5802	0.9546	0.9968
$\rho_{g\pi}$	norm	0.000	0.250	-0.1568	0.2666	-0.3340	-0.0006
$\rho_{u\pi}$	norm	0.000	0.250	-0.0814	0.2952	-0.2357	0.0682

Table 31: Results from Metropolis Hastings for UK (1991:Q3 – 2013:Q4)

C Graphics of Estimated NAIRU, Unemployment Rate and Inflation Rate (without Survey Data)

The following figures show the estimation of NAIRU. The red curve is the actual unemployment rate, the blue- and black-dotted curves show NAIRU and it's 95% confidence interval respectively, and the grey curve traces the dynamics of inflation.

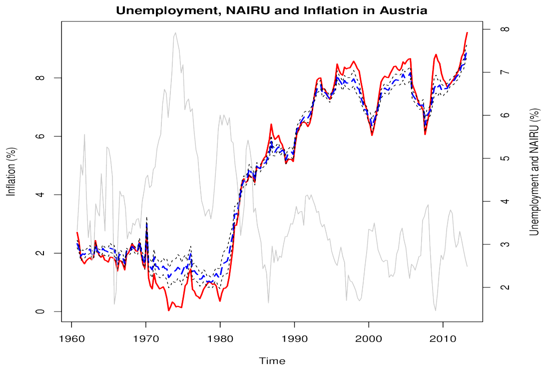

Figure 29: NAIRU for Austria (no survey).

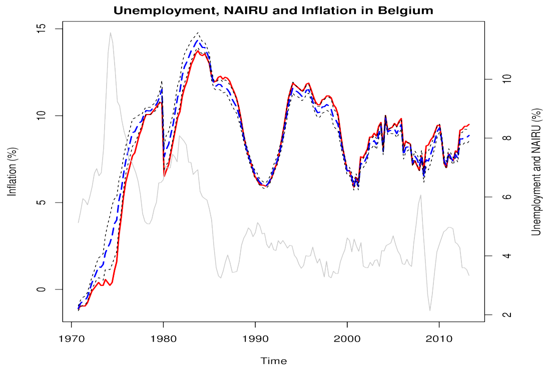

Figure 30: NAIRU for Belgium (no survey).

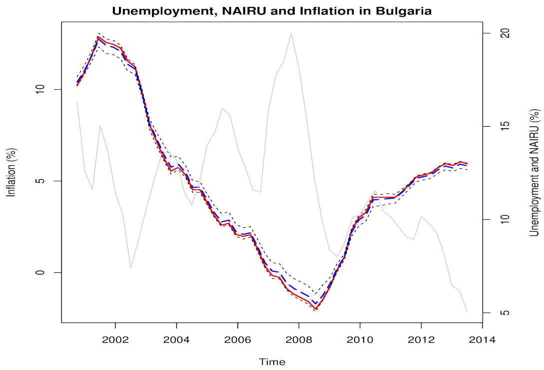

Figure 31: NAIRU for Bulgaria (no survey).

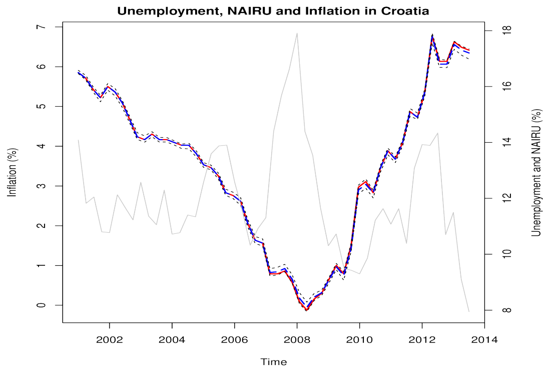

Figure 32: NAIRU for Crotia (no survey).

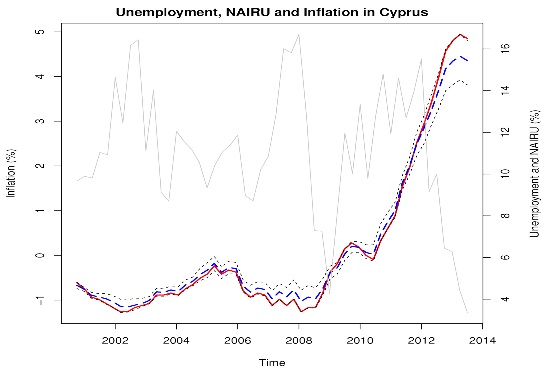

Figure 33: NAIRU for Cyprus (no survey).

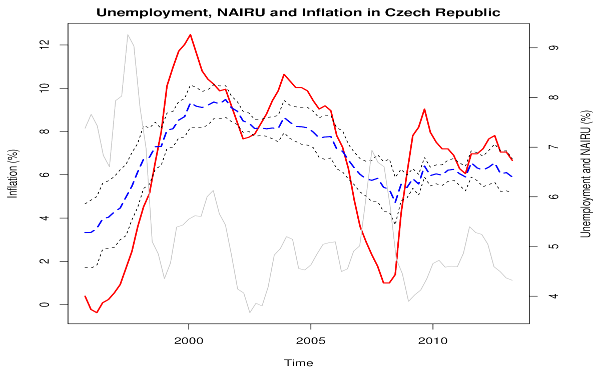

Figure 34: NAIRU for Czech Rep (no survey).

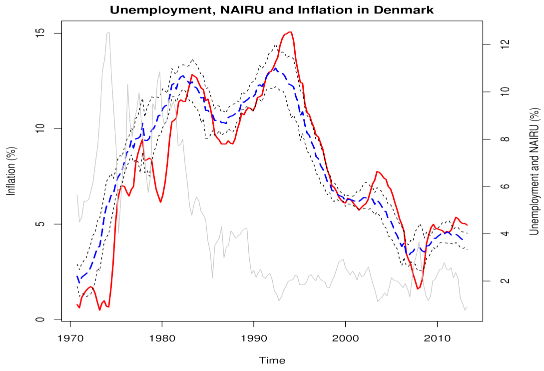

Figure 35: NAIRU for Denmark (no survey).

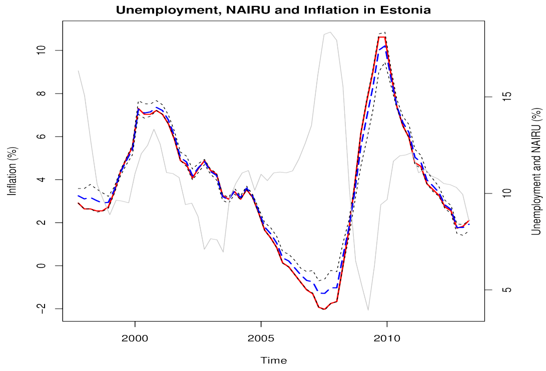

Figure 36: NAIRU for Estonia (no survey).

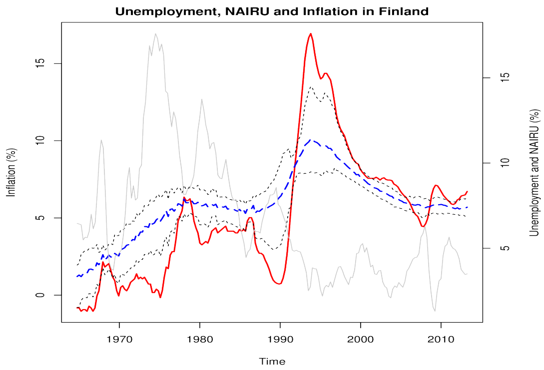

Figure 37: NAIRU for Finland (no survey).

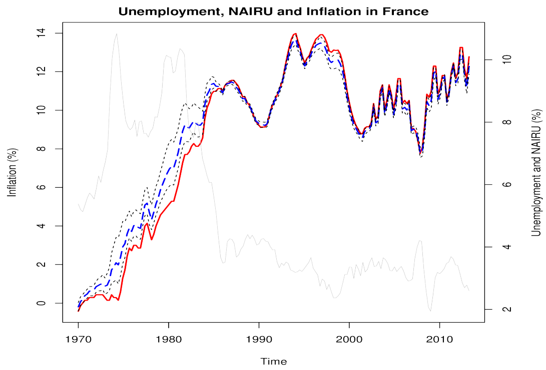

Figure 38: NAIRU for France (no survey).

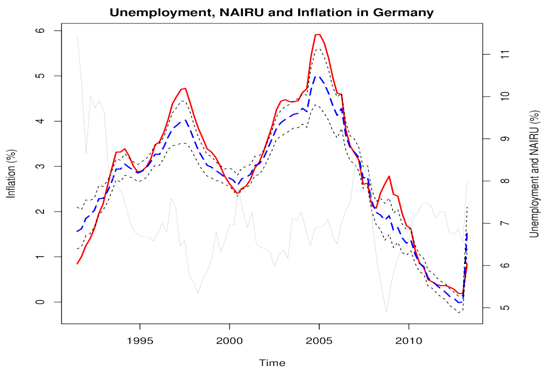

Figure 39: NAIRU for Germany (no survey).

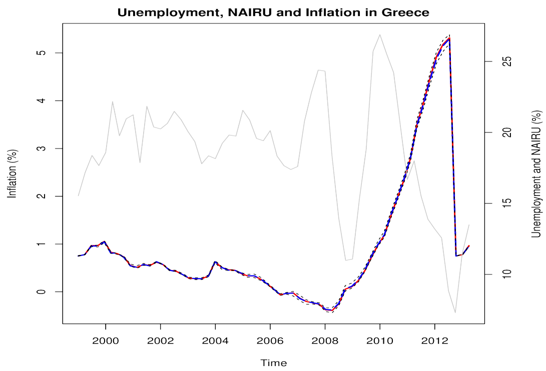

Figure 40: NAIRU for Greece (no survey).

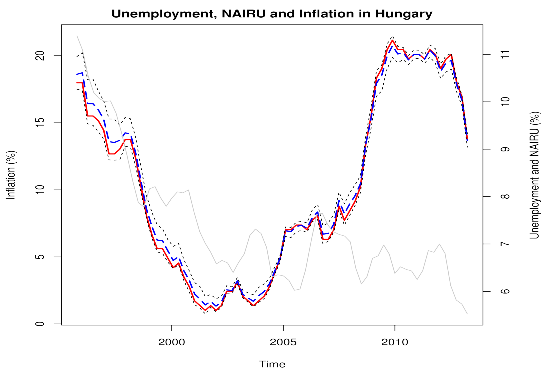

Figure 41: NAIRU for Hungary (no survey).

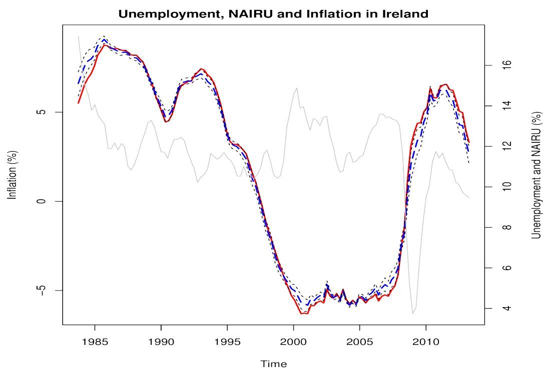

Figure 42: NAIRU for Ireland (no survey).

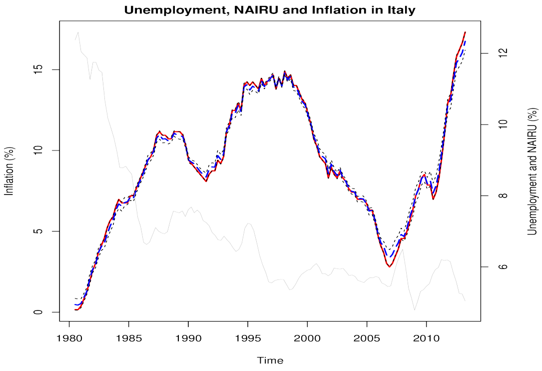

Figure 43: NAIRU for Italy (no survey).

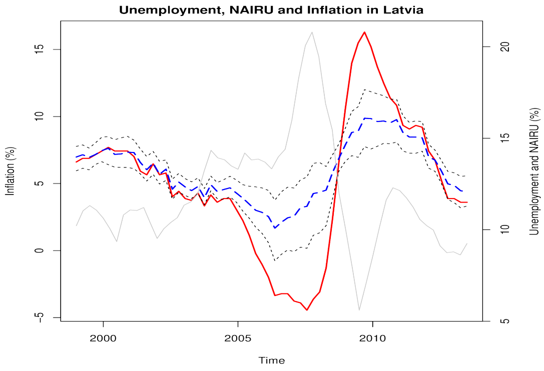

Figure 44: NAIRU for Latvia (no survey).

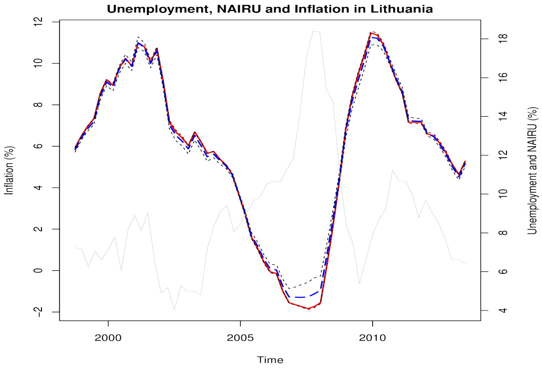

Figure 45: NAIRU for Lithuania (no survey).

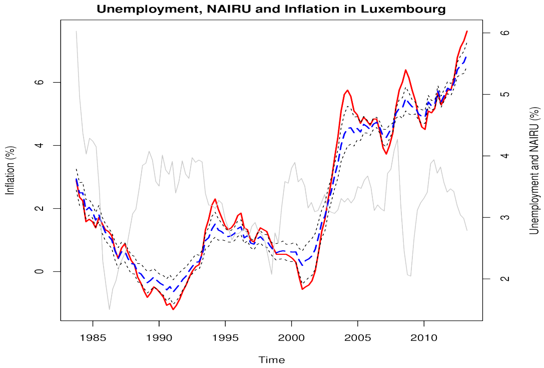

Figure 46: NAIRU for Luxembourg (no survey).

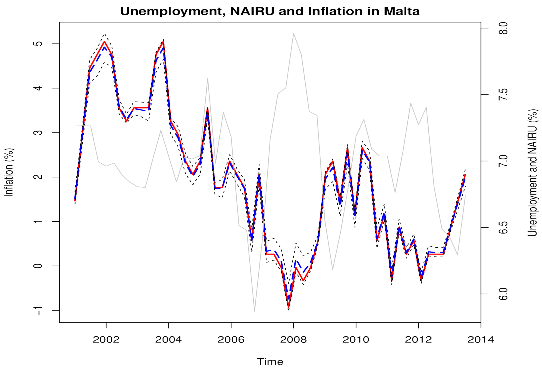

Figure 47: NAIRU for Malta (no survey).

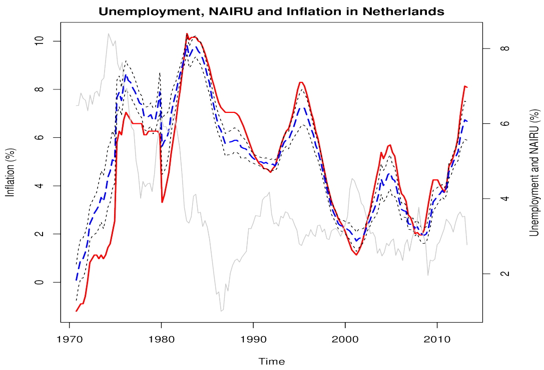

Figure 48: NAIRU for Netherlands (no survey).

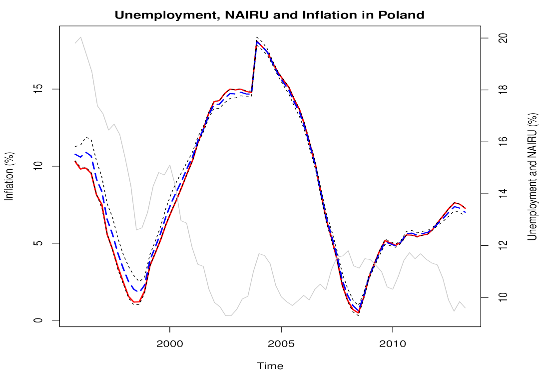

Figure 49: NAIRU for Poland (no survey).

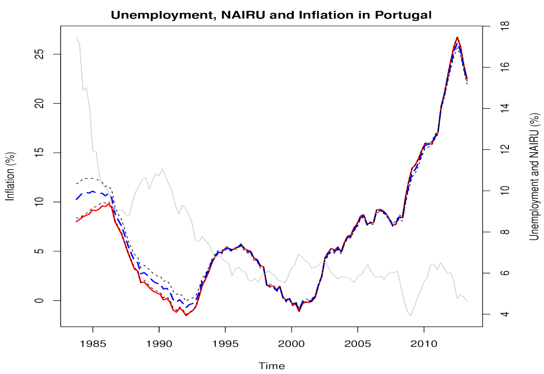

Figure 50: NAIRU for Portugal (no survey).

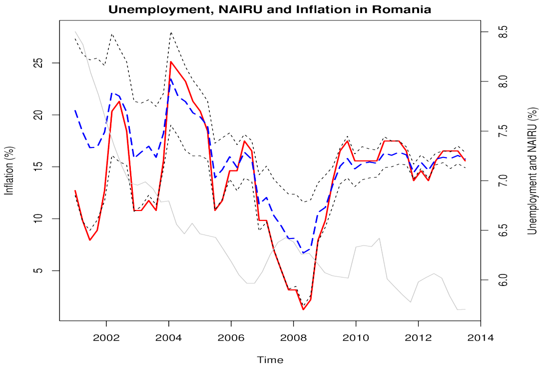

Figure 51: NAIRU for Romania (no survey).

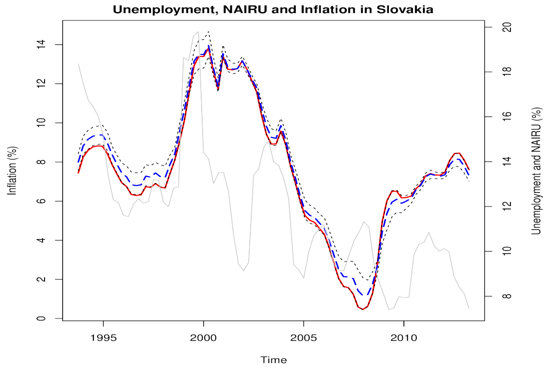

Figure 52: NAIRU for Slovakia (no survey).

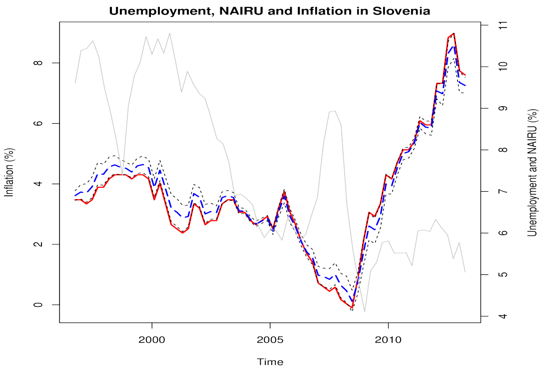

Figure 53: NAIRU for Slovenia (no survey).

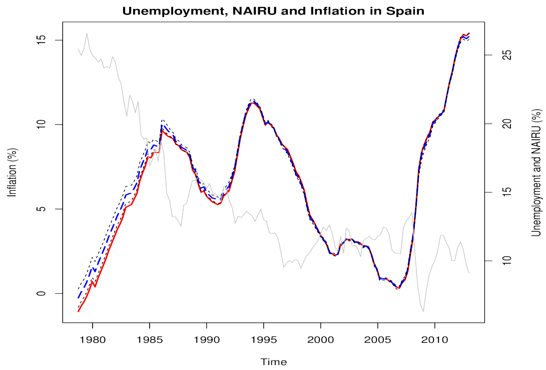

Figure 54: NAIRU for Spain (no survey).

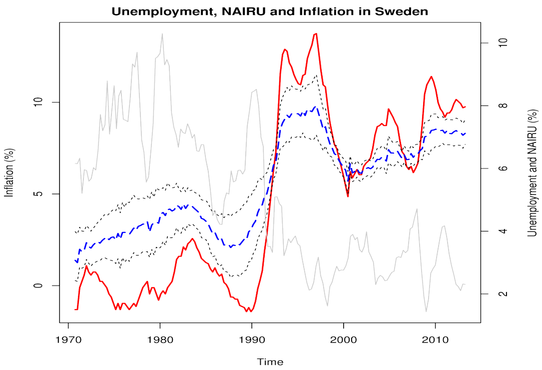

Figure 55: NAIRU for Sweden (no survey).

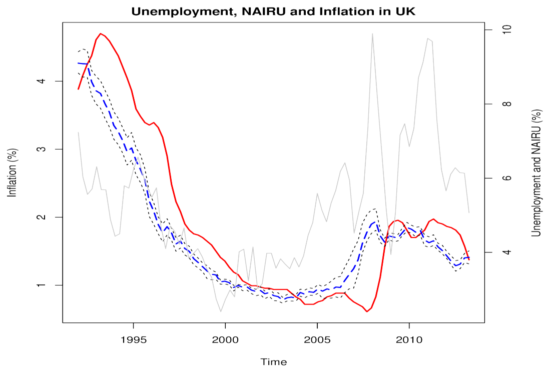

Figure 56: NAIRU for UK (no survey).

D Graphics of Estimated Gaps (without Survey Data)

The following figures show the estimation of output gaps and unemployment gaps, in which two time series of estimated unemployment gap (red curve) and estimated output gap (gery-dotted curve) are drawn together.

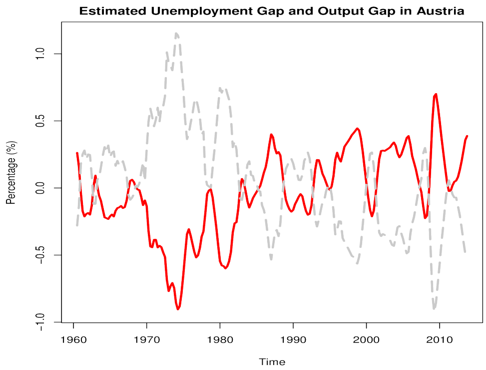

Figure 57: Gaps for Austria (no survey).

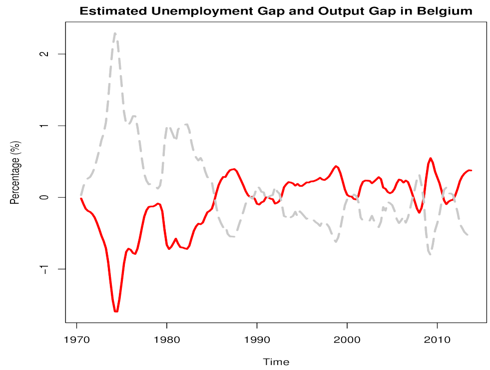

Figure 58: Gaps for Belgium (no survey).

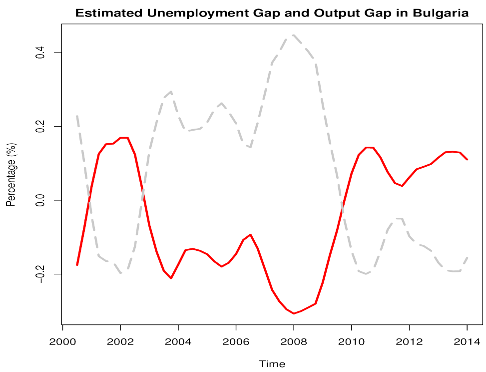

Figure 59: Gaps for Bulgaria (no survey).

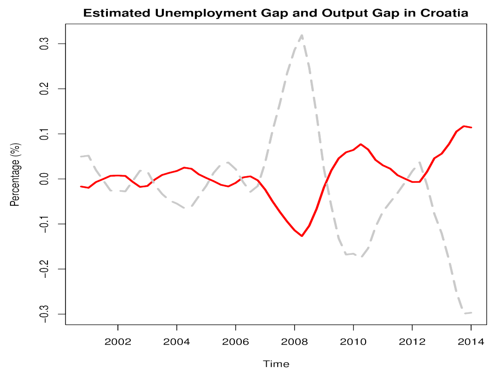

Figure 60: Gaps for Crotia (no survey).

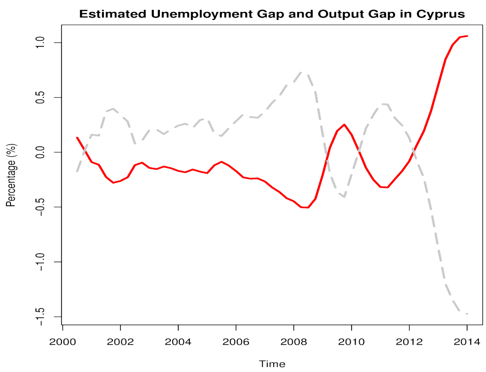

Figure 61: Gaps for Cyprus (no survey).

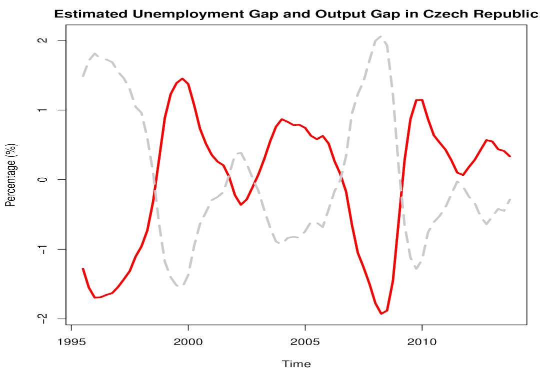

Figure 62: Gaps for Czech Rep (no survey).

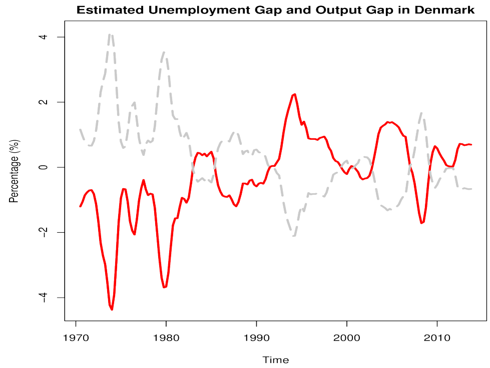

Figure 63: Gaps for Denmark (no survey).

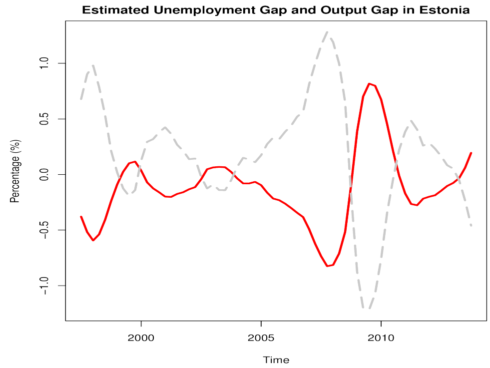

Figure 64: Gaps for Estonia (no survey).

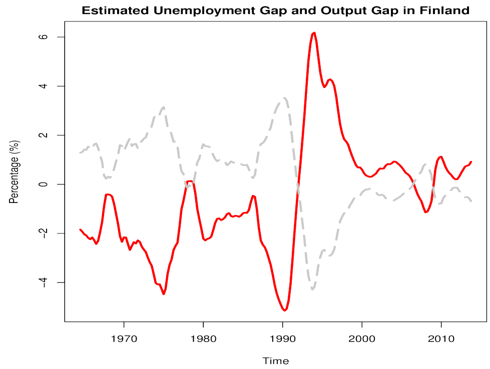

Figure 65: Gaps for Finland (no survey).

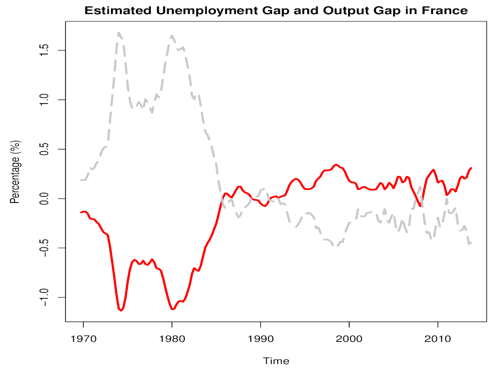

Figure 66: Gaps for France (no survey).

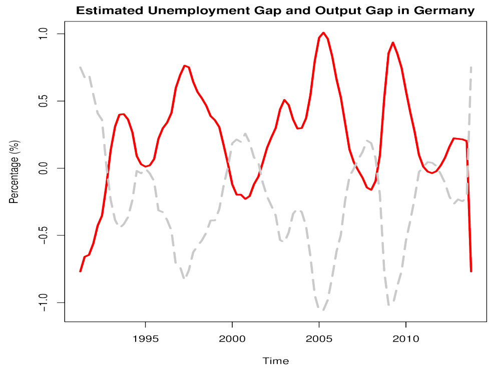

Figure 67: Gaps for Germany (no survey).

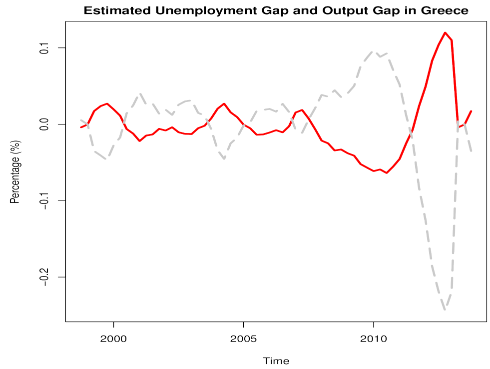

Figure 68: Gaps for Greece (no survey).

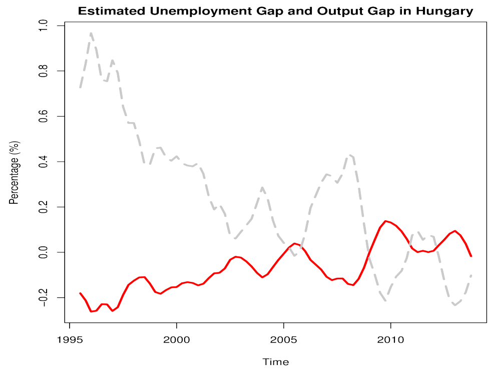

Figure 69: Gaps for Hungary (no survey).

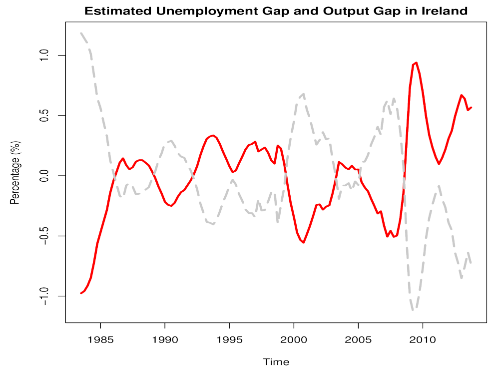

Figure 70: Gaps for Ireland (no survey).

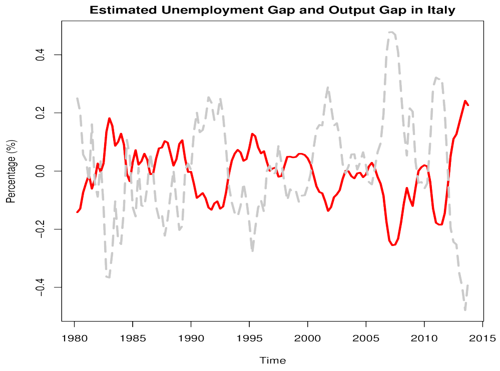

Figure 71: Gaps for Italy (no survey).

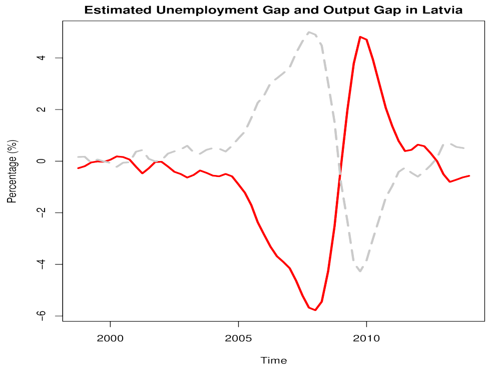

Figure 72: Gaps for Latvia (no survey).

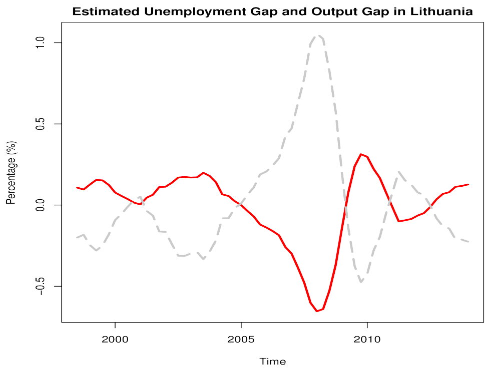

Figure 73: Gaps for Lithuania (no survey).

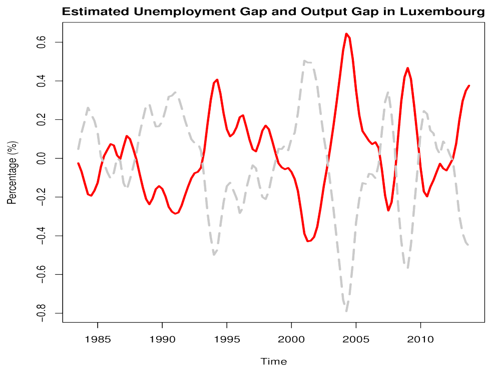

Figure 74: Gaps for Luxembourg (no survey).

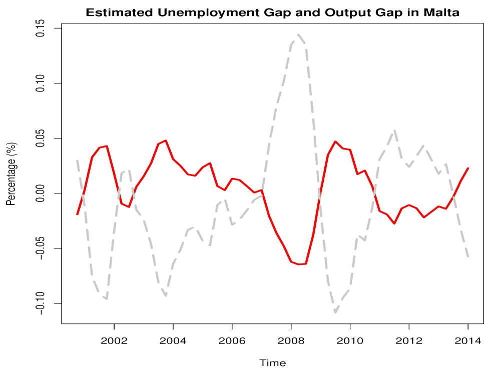

Figure 75: Gaps for Malta (no survey).

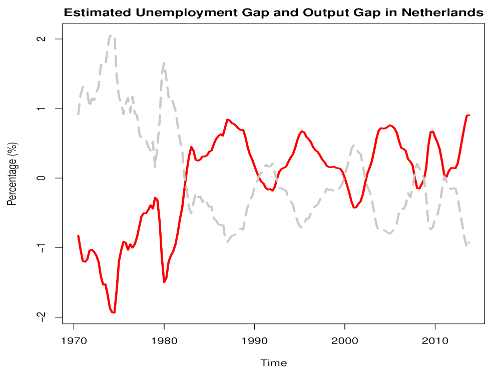

Figure 76: Gaps for Netherlands (no survey).

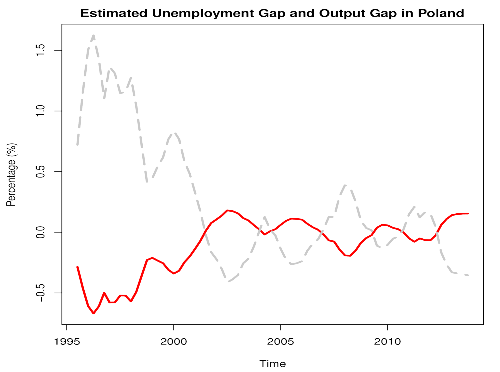

Figure 77: Gaps for Poland (no survey).

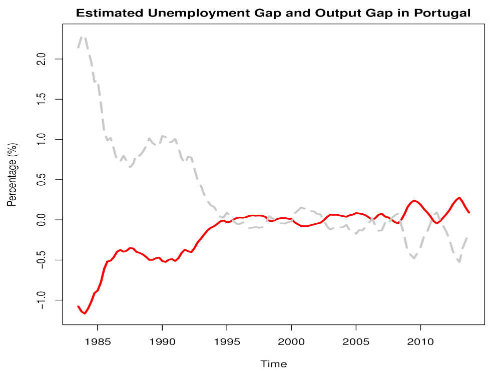

Figure 78: Gaps for Portugal (no survey).

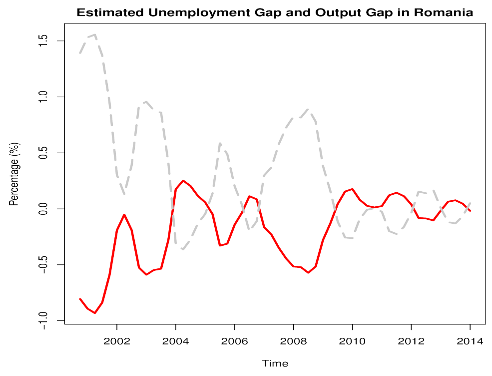

Figure 79: Gaps for Romania (no survey).

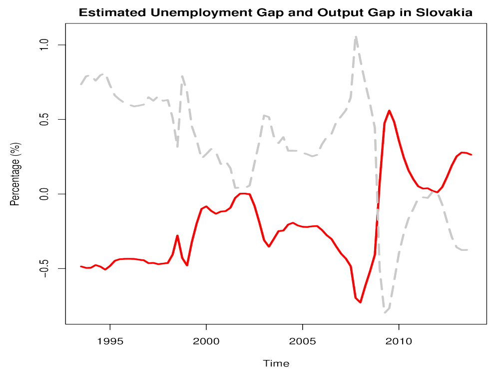

Figure 80: Gaps for Slovakia (no survey).

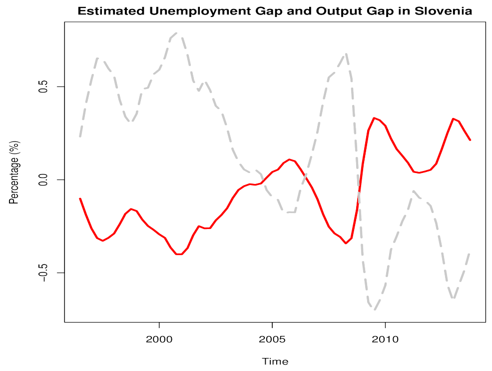

Figure 81: Gaps for Slovenia (no survey).

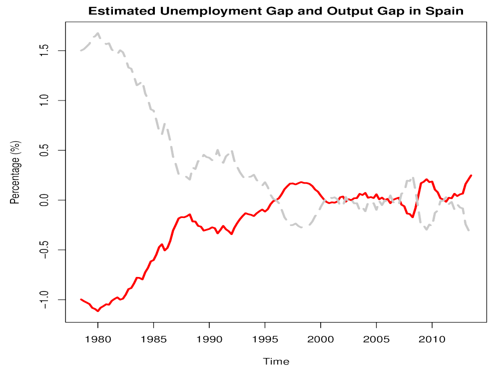

Figure 82: Gaps for Spain (no survey).

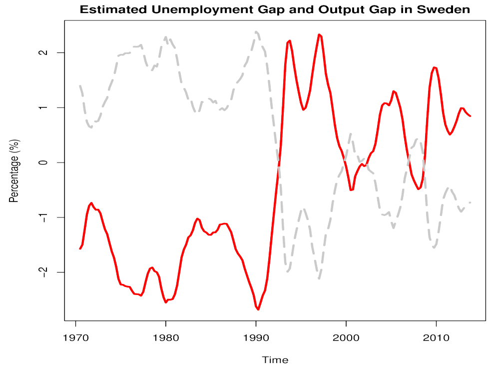

Figure 83: Gaps for Sweden (no survey).

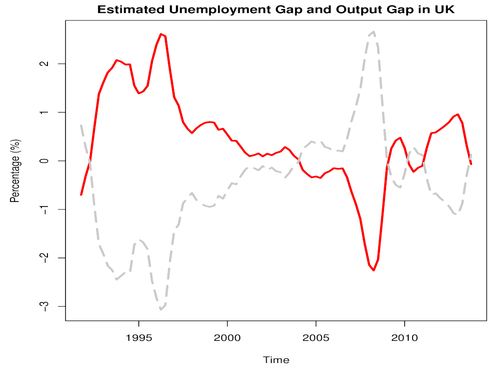

Figure 84: Gaps for UK (no survey).

E Estimation for Paramters, Standard Deviation of Shocks, and the Correlation of Structural Shocks (with Survey Data)

Below are Bayesian estimation results for paramters, standard deviations of shocks, and the correlations of structural shocks (with Survey Data). Note that some prior specifications are different from others. If so, we mark the corresponding entries red.

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8321	0.0167	0.7989	0.8582
ζ	gamma	0.500	0.2000	0.1450	0.0507	0.0682	0.2367
μ_y	gamma	3.060	0.3000	2.4538	0.1842	2.1409	2.7660
μ_π	gamma	3.060	0.3000	2.1774	0.1709	1.9227	2.4371
ρ_1	norm	1.350	0.0200	1.3587	0.0183	1.3300	1.3903
ρ_2	norm	-0.500	0.0200	-0.4836	0.0172	-0.5123	-0.4580
η_0	norm	-0.400	0.2000	-0.4399	0.1612	-0.7043	-0.1815
η_1	norm	0.000	0.2000	0.2636	0.1244	0.0669	0.5038
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0011	0.0003	0.0007	0.0015
σ_n	inverse-gamma	0.007	0.0010	0.0066	0.0004	0.0059	0.0073
σ_π	inverse-gamma	0.008	0.0010	0.0058	0.0004	0.0051	0.0065
σ_u	inverse-gamma	0.002	0.0010	0.0018	0.0001	0.0015	0.0020
σ_e	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0006	0.0013
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.1435	0.1333	-0.3393	0.0451
ρ_{nu}	norm	0.000	0.2500	-0.4438	0.0898	-0.6032	-0.3057
$\rho_{n\pi}$	norm	0.000	0.2500	0.2115	0.1210	0.0471	0.3913
ρ_{gu}	norm	0.000	0.2500	-0.0558	0.1578	-0.2995	0.1659
$\rho_{g\pi}$	norm	0.000	0.2500	-0.2907	0.1490	-0.5125	-0.0736
$\rho_{u\pi}$	norm	0.000	0.2500	-0.2974	0.1108	-0.4762	-0.1169

Table 32: Results from Metropolis Hastings for Austria (1995:Q4 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8485	0.0166	0.8229	0.8736
ζ	gamma	0.500	0.2000	0.0898	0.0341	0.0341	0.1431
μ_y	gamma	3.060	0.3000	2.3877	0.1735	2.1183	2.6722
μ_π	gamma	3.060	0.3000	2.4989	0.1834	2.2229	2.7661
ρ_1	norm	1.350	0.0200	1.3774	0.0176	1.3498	1.4052
ρ_2	norm	-0.500	0.0200	-0.4638	0.0158	-0.4867	-0.4352
η_0	norm	-0.400	0.2000	-0.4920	0.1843	-0.7842	-0.2175
η_1	norm	0.000	0.2000	-0.0922	0.1625	-0.3388	0.1823
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0007	0.0013
σ_n	inverse-gamma	0.007	0.0010	0.0069	0.0004	0.0062	0.0075
σ_π	inverse-gamma	0.008	0.0010	0.0056	0.0003	0.0051	0.0062
σ_u	inverse-gamma	0.002	0.0010	0.0032	0.0002	0.0028	0.0035
σ_e	inverse-gamma	0.002	0.0010	0.0009	0.0002	0.0006	0.0012
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0588	0.1112	-0.2303	0.0864
ρ_{nu}	norm	0.000	0.2500	-0.2022	0.0851	-0.3529	-0.0514
$\rho_{n\pi}$	norm	0.000	0.2500	0.1368	0.0973	-0.0203	0.2927
ρ_{gu}	norm	0.000	0.2500	0.0603	0.1224	-0.1529	0.2383
$\rho_{g\pi}$	norm	0.000	0.2500	0.0210	0.1352	-0.1724	0.2401
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1302	0.0943	-0.2836	0.0174

Table 33: Results from Metropolis Hastings for Belgium (1985:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8542	0.0163	0.8306	0.8814
ζ	gamma	0.500	0.2000	0.0633	0.0236	0.0306	0.1010
μ_y	gamma	3.060	0.3000	2.5603	0.2218	2.1976	2.9013
μ_π	gamma	3.060	0.3000	2.5369	0.1277	2.3234	2.7355
ρ_1	norm	1.350	0.0200	1.3678	0.0175	1.3430	1.3966
ρ_2	norm	-0.500	0.0200	-0.4744	0.0155	-0.5003	-0.4530
η_0	norm	-0.400	0.2000	-0.5241	0.1797	-0.8199	-0.2557
η_1	norm	0.000	0.2000	-0.1449	0.1559	-0.4029	0.1215
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0011	0.0003	0.0007	0.0014
σ_n	inverse-gamma	0.007	0.0010	0.0119	0.0007	0.0107	0.0131
σ_π	inverse-gamma	0.008	0.0010	0.0060	0.0003	0.0054	0.0066
σ_u	inverse-gamma	0.002	0.0010	0.0029	0.0002	0.0026	0.0032
σ_e	inverse-gamma	0.002	0.0010	0.0008	0.0001	0.0006	0.0011
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0045	0.0938	-0.1686	0.1316
ρ_{nu}	norm	0.000	0.2500	-0.1155	0.0800	-0.2456	0.0126
$\rho_{n\pi}$	norm	0.000	0.2500	0.0837	0.0864	-0.0528	0.2063
ρ_{gu}	norm	0.000	0.2500	0.1039	0.1228	-0.0852	0.2911
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1680	0.1235	-0.3475	0.0083
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0431	0.0939	-0.2117	0.1023

Table 34: Results from Metropolis Hastings for Denmark (1985:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8476	0.0183	0.8162	0.8737
ζ	gamma	0.500	0.2000	0.1245	0.0436	0.0466	0.1958
μ_y	gamma	3.060	0.3000	2.6789	0.2370	2.3193	3.0199
μ_π	gamma	3.060	0.3000	2.3722	0.1763	2.0992	2.6878
ρ_1	norm	1.350	0.0200	1.3649	0.0176	1.3404	1.3945
ρ_2	norm	-0.500	0.0200	-0.4770	0.0158	-0.4993	-0.4527
η_0	norm	-0.400	0.2000	-0.7620	0.1619	-1.0191	-0.5039
η_1	norm	0.000	0.2000	-0.1346	0.1507	-0.3692	0.0772
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0014	0.0004	0.0008	0.0018
σ_n	inverse-gamma	0.007	0.0010	0.0115	0.0008	0.0102	0.0127
σ_π	inverse-gamma	0.008	0.0010	0.0058	0.0004	0.0051	0.0065
σ_u	inverse-gamma	0.002	0.0010	0.0023	0.0002	0.0020	0.0025
σ_e	inverse-gamma	0.002	0.0010	0.0012	0.0002	0.0007	0.0016
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.0426	0.1125	-0.1134	0.1926
ρ_{nu}	norm	0.000	0.2500	-0.3316	0.0930	-0.4521	-0.1923
$\rho_{n\pi}$	norm	0.000	0.2500	0.3428	0.0998	0.1830	0.4903
ρ_{gu}	norm	0.000	0.2500	0.4074	0.1855	0.1707	0.6269
$\rho_{g\pi}$	norm	0.000	0.2500	-0.0454	0.1542	-0.2957	0.1546
$\rho_{u\pi}$	norm	0.000	0.2500	-0.3775	0.1127	-0.5670	-0.2086

Table 35: Results from Metropolis Hastings for Finland (1996:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8620	0.0159	0.8364	0.8894
ζ	gamma	0.500	0.2000	0.0924	0.0329	0.0322	0.1427
μ_y	gamma	3.060	0.3000	2.3015	0.1571	2.0944	2.5307
μ_π	gamma	3.060	0.3000	2.3874	0.1837	2.0987	2.6928
ρ_1	norm	1.350	0.0200	1.3803	0.0172	1.3536	1.4071
ρ_2	norm	-0.500	0.0200	-0.4562	0.0152	-0.4775	-0.4327
η_0	norm	-0.400	0.2000	-0.4311	0.1889	-0.7406	-0.1083
η_1	norm	0.000	0.2000	-0.1308	0.1724	-0.4252	0.1624
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0008	0.0002	0.0006	0.0011
σ_n	inverse-gamma	0.007	0.0010	0.0058	0.0003	0.0053	0.0064
σ_π	inverse-gamma	0.008	0.0010	0.0049	0.0003	0.0045	0.0053
σ_u	inverse-gamma	0.002	0.0010	0.0035	0.0002	0.0031	0.0039
σ_e	inverse-gamma	0.002	0.0010	0.0009	0.0002	0.0006	0.0012
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.0513	0.1183	-0.1432	0.2294
ρ_{nu}	norm	0.000	0.2500	-0.2745	0.0882	-0.4171	-0.1454
$\rho_{n\pi}$	norm	0.000	0.2500	0.1868	0.1150	0.0042	0.3795
ρ_{gu}	norm	0.000	0.2500	0.0233	0.1115	-0.1569	0.1916
$\rho_{g\pi}$	norm	0.000	0.2500	-0.0408	0.1566	-0.2723	0.1944
$\rho_{u\pi}$	norm	0.000	0.2500	-0.3653	0.0910	-0.5217	-0.2146

Table 36: Results from Metropolis Hastings for France (1985:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8381	0.0168	0.8100	0.8631
ζ	gamma	0.500	0.2000	0.1585	0.0834	0.0596	0.2652
μ_y	gamma	3.060	0.3000	2.4528	0.2038	2.1205	2.8171
μ_π	gamma	3.060	0.3000	2.6515	0.2355	2.2586	3.0387
ρ_1	norm	1.350	0.0200	1.3725	0.0215	1.3492	1.3994
ρ_2	norm	-0.500	0.0200	-0.4648	0.0171	-0.4872	-0.4373
η_0	norm	-0.400	0.2000	-0.4708	0.1823	-0.7432	-0.2015
η_1	norm	0.000	0.2000	-0.0116	0.1676	-0.3391	0.2705
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0010	0.0003	0.0007	0.0013
σ_n	inverse-gamma	0.007	0.0010	0.0085	0.0005	0.0076	0.0094
σ_π	inverse-gamma	0.008	0.0010	0.0058	0.0004	0.0053	0.0065
σ_u	inverse-gamma	0.002	0.0010	0.0027	0.0002	0.0024	0.0030
σ_e	inverse-gamma	0.002	0.0010	0.0011	0.0002	0.0006	0.0016
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.2466	0.1090	0.0724	0.3995
ρ_{nu}	norm	0.000	0.2500	-0.2511	0.0906	-0.3790	-0.1181
$\rho_{n\pi}$	norm	0.000	0.2500	0.0290	0.1048	-0.1473	0.1811
ρ_{gu}	norm	0.000	0.2500	0.1279	0.1258	-0.0536	0.2972
$\rho_{g\pi}$	norm	0.000	0.2500	-0.5606	0.1664	-0.7339	-0.3549
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1927	0.1052	-0.3581	-0.0271

Table 37: Results from Metropolis Hastings for Germany (1992:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.7986	0.0212	0.7714	0.8234
ζ	gamma	0.500	0.2000	0.0729	0.0268	0.0280	0.1084
μ_y	gamma	3.060	0.3000	2.9983	0.2931	2.5201	3.4746
μ_π	gamma	3.060	0.3000	2.9259	0.1785	2.5978	3.2116
ρ_1	norm	1.350	0.0200	1.3515	0.0202	1.3228	1.3852
ρ_2	norm	-0.500	0.0200	-0.5025	0.0211	-0.5299	-0.4695
η_0	norm	-0.400	0.2000	-0.4078	0.1946	-0.7119	-0.0931
η_1	norm	0.000	0.2000	0.0604	0.1842	-0.1774	0.3137
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0100	0.0015	0.0005	0.0009	0.0021
σ_n	inverse-gamma	0.007	0.0100	0.0529	0.0045	0.0442	0.0597
σ_π	inverse-gamma	0.008	0.0100	0.0155	0.0014	0.0128	0.0181
σ_u	inverse-gamma	0.002	0.0100	0.0073	0.0006	0.0059	0.0086
σ_e	inverse-gamma	0.002	0.0100	0.0009	0.0002	0.0004	0.0013
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.0092	0.1145	-0.1758	0.1853
ρ_{nu}	norm	0.000	0.2500	-0.4222	0.1001	-0.5752	-0.2483
$\rho_{n\pi}$	norm	0.000	0.2500	-0.0877	0.1106	-0.2345	0.0848
ρ_{gu}	norm	0.000	0.2500	-0.1544	0.1272	-0.3453	0.0377
$\rho_{g\pi}$	norm	0.000	0.2500	-0.2316	0.1482	-0.4220	-0.0222
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0800	0.1111	-0.2659	0.0967

Table 38: Results from Metropolis Hastings for Greece (1999:Q3 – 2013:Q1)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8485	0.0182	0.8154	0.8721
ζ	gamma	0.500	0.2000	0.1756	0.0875	0.0699	0.2786
μ_y	gamma	3.060	0.3000	2.8161	0.2317	2.4890	3.2122
μ_π	gamma	3.060	0.3000	3.2021	0.3198	2.6663	3.6563
ρ_1	norm	1.350	0.0200	1.4035	0.0531	1.3823	1.4296
ρ_2	norm	-0.500	0.0200	-0.4320	0.0381	-0.4551	-0.4109
η_0	norm	-0.400	0.2000	-0.3155	0.1943	-0.6227	0.0062
η_1	norm	0.000	0.2000	0.0639	0.1801	-0.2114	0.2925
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0009	0.0005	0.0007	0.0011
σ_n	inverse-gamma	0.007	0.0010	0.0090	0.0006	0.0080	0.0101
σ_π	inverse-gamma	0.008	0.0010	0.0119	0.0009	0.0105	0.0133
σ_u	inverse-gamma	0.002	0.0010	0.0032	0.0002	0.0028	0.0036
σ_e	inverse-gamma	0.002	0.0010	0.0012	0.0003	0.0008	0.0017
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0884	0.1281	-0.2494	0.0738
ρ_{nu}	norm	0.000	0.2500	-0.2556	0.0952	-0.4207	-0.1185
$\rho_{n\pi}$	norm	0.000	0.2500	0.0966	0.0944	-0.0400	0.2553
ρ_{gu}	norm	0.000	0.2500	0.0260	0.1322	-0.1704	0.2513
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1394	0.2465	-0.3899	0.1139
$\rho_{u\pi}$	norm	0.000	0.2500	0.0736	0.0948	-0.0841	0.1928

Table 39: Results from Metropolis Hastings for Hungary (1996:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8526	0.0183	0.8263	0.8780
ζ	gamma	0.500	0.2000	0.0731	0.0272	0.0276	0.1189
μ_y	gamma	3.060	0.3000	3.2640	0.2776	2.8034	3.7130
μ_π	gamma	3.060	0.3000	2.7522	0.1898	2.4511	3.0383
ρ_1	norm	1.350	0.0200	1.3839	0.0171	1.3557	1.4106
ρ_2	norm	-0.500	0.0200	-0.4615	0.0148	-0.4857	-0.4324
η_0	norm	-0.400	0.2000	-0.5068	0.1893	-0.8097	-0.1679
η_1	norm	0.000	0.2000	-0.1270	0.1703	-0.3839	0.1305
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0010	0.0003	0.0007	0.0014
σ_n	inverse-gamma	0.007	0.0010	0.0155	0.0009	0.0140	0.0171
σ_π	inverse-gamma	0.008	0.0010	0.0067	0.0004	0.0060	0.0073
σ_u	inverse-gamma	0.002	0.0010	0.0045	0.0003	0.0040	0.0049
σ_e	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0006	0.0013
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	0.1078	0.0867	-0.0074	0.2420
ρ_{nu}	norm	0.000	0.2500	-0.3188	0.0721	-0.4426	-0.1719
$\rho_{n\pi}$	norm	0.000	0.2500	0.0755	0.0807	-0.0568	0.1934
ρ_{gu}	norm	0.000	0.2500	-0.0784	0.1116	-0.2489	0.0640
$\rho_{g\pi}$	norm	0.000	0.2500	0.1273	0.1122	-0.0325	0.3063
$\rho_{u\pi}$	norm	0.000	0.2500	-0.3268	0.0803	-0.4614	-0.2060

Table 40: Results from Metropolis Hastings for Ireland (1985:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8519	0.0175	0.8228	0.8831
ζ	gamma	0.500	0.2000	0.1325	0.0425	0.0713	0.2099
μ_y	gamma	3.060	0.3000	2.2306	0.1880	1.9647	2.5784
μ_π	gamma	3.060	0.3000	3.1899	0.3014	2.7014	3.6036
ρ_1	norm	1.350	0.0200	0.1707	0.1145	-0.0213	0.3448
ρ_2	norm	-0.500	1.0000	0.7924	0.1120	0.6279	0.9845
η_0	norm	-0.400	1.0000	-0.3338	0.2642	-0.6126	-0.0533
η_1	norm	0.000	0.2000	-0.0545	0.1925	-0.3723	0.2617
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0100	0.0005	0.0002	0.0003	0.0006
σ_n	inverse-gamma	0.007	0.0100	0.0078	0.0008	0.0069	0.0086
σ_π	inverse-gamma	0.008	0.0100	0.0036	0.0002	0.0031	0.0039
σ_u	inverse-gamma	0.002	0.0100	0.0026	0.0002	0.0023	0.0028
σ_e	inverse-gamma	0.002	0.0100	0.0006	0.0001	0.0004	0.0009
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.1611	0.0929	0.0294	0.2835
ρ_{nu}	norm	0.000	0.2500	-0.2426	0.0827	-0.3561	-0.0913
$\rho_{n\pi}$	norm	0.000	0.2500	0.0946	0.0862	-0.0274	0.2423
ρ_{gu}	norm	0.000	0.2500	-0.0629	0.0977	-0.2083	0.0825
$\rho_{g\pi}$	norm	0.000	0.2500	0.1635	0.1073	-0.0464	0.3381
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0763	0.0862	-0.2027	0.0612

Table 41: Results from Metropolis Hastings for Italy (1985:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8227	0.0168	0.8006	0.8474
ζ	gamma	0.500	0.2000	0.1301	0.0455	0.0615	0.1871
μ_y	gamma	3.060	0.3000	2.9880	0.2744	2.5513	3.4667
μ_π	gamma	3.060	0.3000	2.4181	0.1489	2.1991	2.6441
ρ_1	norm	1.350	0.0200	1.3510	0.0179	1.3220	1.3756
ρ_2	norm	-0.500	0.0200	-0.4959	0.0177	-0.5259	-0.4683
η_0	norm	-0.400	0.2000	-0.2225	0.1787	-0.5067	0.0565
η_1	norm	0.000	0.2000	0.1653	0.1582	-0.0584	0.4577
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0011	0.0002	0.0008	0.0013
σ_n	inverse-gamma	0.007	0.0010	0.0136	0.0011	0.0118	0.0152
σ_π	inverse-gamma	0.008	0.0010	0.0067	0.0005	0.0057	0.0075
σ_u	inverse-gamma	0.002	0.0010	0.0022	0.0002	0.0018	0.0025
σ_e	inverse-gamma	0.002	0.0010	0.0012	0.0002	0.0006	0.0017
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.0359	0.1184	-0.1560	0.1967
ρ_{nu}	norm	0.000	0.2500	-0.1753	0.1053	-0.3340	-0.0181
$\rho_{n\pi}$	norm	0.000	0.2500	0.1528	0.1128	-0.0265	0.3561
ρ_{gu}	norm	0.000	0.2500	0.0792	0.1593	-0.1380	0.3434
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1180	0.1745	-0.3687	0.1442
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0380	0.1328	-0.2288	0.1760

Table 42: Results from Metropolis Hastings for Luxembourg (2002:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8117	0.0176	0.7877	0.8386
ζ	gamma	0.500	0.2000	0.1529	0.0565	0.0595	0.2392
μ_y	gamma	3.060	0.3000	3.2734	0.2360	2.9216	3.6545
μ_π	gamma	3.060	0.3000	2.9079	0.2148	2.5382	3.2511
ρ_1	norm	1.350	0.0200	1.3603	0.0186	1.3330	1.3856
ρ_2	norm	-0.500	0.0200	-0.4841	0.0175	-0.5147	-0.4590
η_0	norm	-0.400	0.2000	-0.4082	0.1906	-0.6549	-0.0835
η_1	norm	0.000	0.2000	-0.0254	0.1812	-0.3322	0.2707
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0014	0.0003	0.0010	0.0019
σ_n	inverse-gamma	0.007	0.0010	0.0066	0.0005	0.0058	0.0075
σ_π	inverse-gamma	0.008	0.0010	0.0078	0.0006	0.0067	0.0088
σ_u	inverse-gamma	0.002	0.0010	0.0051	0.0005	0.0043	0.0060
σ_e	inverse-gamma	0.002	0.0010	0.0012	0.0003	0.0006	0.0016
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.2466	0.1641	-0.5203	-0.0219
ρ_{nu}	norm	0.000	0.2500	-0.2434	0.1217	-0.4504	-0.0360
$\rho_{n\pi}$	norm	0.000	0.2500	0.2720	0.1214	0.0644	0.4339
ρ_{gu}	norm	0.000	0.2500	0.0308	0.1421	-0.2188	0.2728
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1963	0.1542	-0.4496	-0.0085
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1259	0.1155	-0.3007	0.0831

Table 43: Results from Metropolis Hastings for Poland (2001:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8581	0.0180	0.8352	0.8833
ζ	gamma	0.500	0.2000	0.0727	0.0254	0.0331	0.1120
μ_y	gamma	3.060	0.3000	2.7540	0.2164	2.4342	3.1187
μ_π	gamma	3.060	0.3000	3.3168	0.3040	2.8193	3.8182
ρ_1	norm	1.350	0.0200	1.3948	0.0221	1.3691	1.4202
ρ_2	norm	-0.500	0.0200	-0.4394	0.0173	-0.4616	-0.4160
η_0	norm	-0.400	0.2000	-0.4365	0.1897	-0.7288	-0.1620
η_1	norm	0.000	0.2000	0.0196	0.1744	-0.2264	0.3079
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0009	0.0003	0.0006	0.0011
σ_n	inverse-gamma	0.007	0.0010	0.0103	0.0006	0.0093	0.0113
σ_π	inverse-gamma	0.008	0.0010	0.0078	0.0005	0.0070	0.0085
σ_u	inverse-gamma	0.002	0.0010	0.0037	0.0002	0.0034	0.0041
σ_e	inverse-gamma	0.002	0.0010	0.0011	0.0002	0.0006	0.0015
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0154	0.0903	-0.1681	0.1157
ρ_{nu}	norm	0.000	0.2500	-0.3901	0.0718	-0.5295	-0.2740
$\rho_{n\pi}$	norm	0.000	0.2500	0.2032	0.0795	0.0938	0.3452
ρ_{gu}	norm	0.000	0.2500	-0.1734	0.0998	-0.3090	-0.0258
$\rho_{g\pi}$	norm	0.000	0.2500	-0.0529	0.1088	-0.1954	0.1156
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0941	0.0844	-0.2432	0.0407

Table 44: Results from Metropolis Hastings for Portugal (1986:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8300	0.0172	0.8025	0.8587
ζ	gamma	0.500	0.2000	0.1137	0.0410	0.0558	0.1795
μ_y	gamma	3.060	0.3000	2.8734	0.2482	2.4140	3.2441
μ_π	gamma	3.060	0.3000	3.2884	0.3012	2.8447	3.8121
ρ_1	norm	1.350	0.0200	1.3877	0.0170	1.3619	1.4127
ρ_2	norm	-0.500	0.0200	-0.4540	0.0149	-0.4730	-0.4281
η_0	norm	-0.400	0.2000	-0.3857	0.1894	-0.7025	-0.1067
η_1	norm	0.000	0.2000	-0.0195	0.1781	-0.2749	0.2452
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0011	0.0002	0.0007	0.0015
σ_n	inverse-gamma	0.007	0.0010	0.0110	0.0008	0.0097	0.0123
σ_π	inverse-gamma	0.008	0.0010	0.0091	0.0007	0.0079	0.0102
σ_u	inverse-gamma	0.002	0.0010	0.0037	0.0003	0.0033	0.0043
σ_e	inverse-gamma	0.002	0.0010	0.0012	0.0003	0.0006	0.0018
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	0.2035	0.1025	0.0481	0.3589
ρ_{nu}	norm	0.000	0.2500	-0.1824	0.0954	-0.3307	-0.0250
$\rho_{n\pi}$	norm	0.000	0.2500	0.0491	0.0943	-0.1186	0.1776
ρ_{gu}	norm	0.000	0.2500	-0.0494	0.1219	-0.2615	0.1519
$\rho_{g\pi}$	norm	0.000	0.2500	-0.2229	0.1303	-0.4348	-0.0336
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0736	0.1009	-0.2167	0.0887

Table 45: Results from Metropolis Hastings for Slovenia (1997:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8444	0.0169	0.8196	0.8682
ζ	gamma	0.500	0.2000	0.0452	0.0167	0.0187	0.0714
μ_y	gamma	3.060	0.3000	2.7509	0.1870	2.4189	3.0336
μ_π	gamma	3.060	0.3000	3.2971	0.2224	2.9210	3.6536
ρ_1	norm	1.350	0.0200	1.3824	0.0171	1.3550	1.4069
ρ_2	norm	-0.500	0.0200	-0.4579	0.0147	-0.4811	-0.4354
η_0	norm	-0.400	0.2000	-0.4867	0.1942	-0.7839	-0.1874
η_1	norm	0.000	0.2000	0.0000	0.1821	-0.2826	0.2460
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0009	0.0002	0.0007	0.0012
σ_n	inverse-gamma	0.007	0.0010	0.0082	0.0005	0.0075	0.0091
σ_π	inverse-gamma	0.008	0.0010	0.0081	0.0005	0.0074	0.0090
σ_u	inverse-gamma	0.002	0.0010	0.0059	0.0004	0.0052	0.0065
σ_e	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0006	0.0014
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	-0.0368	0.0960	-0.1820	0.1208
ρ_{nu}	norm	0.000	0.2500	-0.5476	0.0628	-0.6669	-0.4421
$\rho_{n\pi}$	norm	0.000	0.2500	0.1154	0.0826	-0.0116	0.2712
ρ_{gu}	norm	0.000	0.2500	-0.1559	0.0946	-0.3135	0.0356
$\rho_{g\pi}$	norm	0.000	0.2500	-0.0818	0.1101	-0.2480	0.0893
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1759	0.0822	-0.3200	-0.0498

Table 46: Results from Metropolis Hastings for Spain (1986:Q3 – 2013:Q3)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8482	0.0172	0.8201	0.8752
ζ	gamma	0.500	0.2000	0.0912	0.0326	0.0320	0.1447
μ_y	gamma	3.060	0.3000	2.7398	0.2321	2.3607	3.0729
μ_π	gamma	3.060	0.3000	2.2667	0.2563	1.8745	2.6555
ρ_1	norm	1.350	0.0200	1.3753	0.0183	1.3494	1.4008
ρ_2	norm	-0.500	0.0200	-0.4613	0.0160	-0.4845	-0.4344
η_0	norm	-0.400	0.2000	-0.6213	0.1860	-0.8682	-0.3436
η_1	norm	0.000	0.2000	-0.0743	0.1651	-0.3804	0.1737
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0011	0.0003	0.0008	0.0014
σ_n	inverse-gamma	0.007	0.0010	0.0093	0.0006	0.0083	0.0105
σ_π	inverse-gamma	0.008	0.0010	0.0067	0.0005	0.0059	0.0074
σ_u	inverse-gamma	0.002	0.0010	0.0028	0.0002	0.0025	0.0032
σ_e	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0006	0.0013
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0158	0.1132	-0.1761	0.1625
ρ_{nu}	norm	0.000	0.2500	-0.2872	0.0928	-0.4444	-0.1268
$\rho_{n\pi}$	norm	0.000	0.2500	0.2784	0.0981	0.1333	0.4432
ρ_{gu}	norm	0.000	0.2500	-0.0783	0.1508	-0.2885	0.1253
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1120	0.1396	-0.3030	0.1305
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1720	0.1070	-0.3264	0.0123

Table 47: Results from Metropolis Hastings for Sweden (1995:Q4 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
Paramter Estimation							
α	norm	0.800	0.0200	0.8192	0.0174	0.7954	0.8477
ζ	gamma	0.500	0.2000	0.1052	0.0388	0.0430	0.1690
μ_y	gamma	3.060	0.3000	2.8307	0.2199	2.4733	3.2210
μ_π	gamma	3.060	0.3000	3.0815	0.2846	2.6273	3.5580
ρ_1	norm	1.350	0.0200	1.3832	0.0175	1.3598	1.4140
ρ_2	norm	-0.500	0.0200	-0.4543	0.0152	-0.4812	-0.4331
η_0	norm	-0.400	0.2000	-0.5963	0.1807	-0.8672	-0.3142
η_1	norm	0.000	0.2000	-0.1729	0.1517	-0.3881	0.0669
Estimation of the Standard Deviation of Structual Shocks							
σ_g	inverse-gamma	0.002	0.0010	0.0014	0.0004	0.0009	0.0019
σ_n	inverse-gamma	0.007	0.0010	0.0088	0.0006	0.0078	0.0099
σ_π	inverse-gamma	0.008	0.0010	0.0108	0.0008	0.0094	0.0122
σ_u	inverse-gamma	0.002	0.0010	0.0032	0.0002	0.0028	0.0035
σ_e	inverse-gamma	0.002	0.0010	0.0013	0.0003	0.0006	0.0020
Estimation of the Correlation of Structual Shocks							
ρ_{ng}	norm	0.000	0.2500	-0.0316	0.1113	-0.2317	0.1272
ρ_{nu}	norm	0.000	0.2500	-0.4559	0.0840	-0.6321	-0.3162
$\rho_{n\pi}$	norm	0.000	0.2500	0.0843	0.0925	-0.0827	0.2215
ρ_{gu}	norm	0.000	0.2500	0.0655	0.1598	-0.1780	0.3214
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1169	0.1192	-0.3339	0.0557
$\rho_{u\pi}$	norm	0.000	0.2500	-0.1138	0.0954	-0.2960	0.0345

Table 48: Results from Metropolis Hastings for Czech Republic (1996:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8487	0.0161	0.8265	0.8755
ζ	gamma	0.500	0.2000	0.0891	0.0311	0.0325	0.1487
μ_y	gamma	3.060	0.3000	2.5470	0.1809	2.2752	2.8367
μ_π	gamma	3.060	0.3000	2.2283	0.1508	1.9568	2.4538
ρ_1	norm	1.350	0.0200	1.3698	0.0174	1.3404	1.3941
ρ_2	norm	-0.500	0.0200	-0.4696	0.0151	-0.4960	-0.4453
η_0	norm	-0.400	0.2000	-0.5496	0.1655	-0.7958	-0.2602
η_1	norm	0.000	0.2000	-0.1014	0.1350	-0.3216	0.1301
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0007	0.0013
σ_n	inverse-gamma	0.007	0.0010	0.0074	0.0004	0.0067	0.0082
σ_π	inverse-gamma	0.008	0.0010	0.0056	0.0003	0.0051	0.0062
σ_u	inverse-gamma	0.002	0.0010	0.0020	0.0001	0.0018	0.0023
σ_e	inverse-gamma	0.002	0.0010	0.0009	0.0002	0.0006	0.0013
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	-0.0792	0.1000	-0.2478	0.0757
ρ_{nu}	norm	0.000	0.2500	-0.3414	0.0768	-0.4526	-0.1979
$\rho_{n\pi}$	norm	0.000	0.2500	0.1272	0.0942	-0.0284	0.3030
ρ_{gu}	norm	0.000	0.2500	0.1239	0.1301	-0.0931	0.3037
$\rho_{g\pi}$	norm	0.000	0.2500	-0.2217	0.1206	-0.3955	-0.0497
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0585	0.0952	-0.2038	0.1039

Table 49: Results from Metropolis Hastings for Netherlands (1985:Q1 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.7988	0.0178	0.7718	0.8306
ζ	gamma	0.500	0.2000	0.1131	0.0438	0.0472	0.1714
μ_y	gamma	3.060	0.3000	3.1512	0.2839	2.6108	3.6006
μ_π	gamma	3.060	0.3000	3.2153	0.3014	2.7203	3.6852
ρ_1	norm	1.350	0.0200	1.3856	0.0172	1.3623	1.4091
ρ_2	norm	-0.500	0.0200	-0.4552	0.0155	-0.4810	-0.4322
η_0	norm	-0.400	0.2000	-0.3305	0.1936	-0.6862	-0.0599
η_1	norm	0.000	0.2000	0.0098	0.1834	-0.2506	0.2985
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0015	0.0003	0.0010	0.0021
σ_n	inverse-gamma	0.007	0.0010	0.0150	0.0011	0.0129	0.0165
σ_π	inverse-gamma	0.008	0.0010	0.0132	0.0010	0.0114	0.0148
σ_u	inverse-gamma	0.002	0.0010	0.0060	0.0005	0.0051	0.0068
σ_e	inverse-gamma	0.002	0.0010	0.0014	0.0003	0.0007	0.0022
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	-0.0708	0.1031	-0.2437	0.0796
ρ_{nu}	norm	0.000	0.2500	-0.2688	0.0945	-0.4171	-0.1237
$\rho_{n\pi}$	norm	0.000	0.2500	0.0482	0.0905	-0.0892	0.1922
ρ_{gu}	norm	0.000	0.2500	0.0822	0.1202	-0.0926	0.2536
$\rho_{g\pi}$	norm	0.000	0.2500	-0.1713	0.1216	-0.3679	0.0062
$\rho_{u\pi}$	norm	0.000	0.2500	0.0983	0.0976	-0.0658	0.2259

Table 50: Results from Metropolis Hastings for Slovakia (1999:Q2 – 2013:Q4)

	Prior	Prior Mean	Prior S.d.	Posterior Mean	Po.Sd.	5%	95%
			Paramter Estimation				
α	norm	0.800	0.0200	0.8581	0.0160	0.8337	0.8856
ζ	gamma	0.500	0.2000	0.0532	0.0201	0.0200	0.0842
μ_y	gamma	3.060	0.3000	2.4230	0.1684	2.1297	2.6818
μ_π	gamma	3.060	0.3000	3.0495	0.2298	2.7239	3.3664
ρ_1	norm	1.350	0.0200	1.3851	0.0180	1.3580	1.4091
ρ_2	norm	-0.500	0.0200	-0.4470	0.0147	-0.4703	-0.4254
η_0	norm	-0.400	0.2000	-0.5138	0.1863	-0.8203	-0.2130
η_1	norm	0.000	0.2000	0.0508	0.1568	-0.1823	0.2825
			Estimation of the Standard Deviation of Structual Shocks				
σ_g	inverse-gamma	0.002	0.0010	0.0009	0.0002	0.0006	0.0011
σ_n	inverse-gamma	0.007	0.0010	0.0074	0.0004	0.0066	0.0080
σ_π	inverse-gamma	0.008	0.0010	0.0072	0.0004	0.0065	0.0078
σ_u	inverse-gamma	0.002	0.0010	0.0027	0.0002	0.0024	0.0030
σ_e	inverse-gamma	0.002	0.0010	0.0010	0.0002	0.0006	0.0014
			Estimation of the Correlation of Structual Shocks				
ρ_{ng}	norm	0.000	0.2500	-0.1772	0.0942	-0.3572	-0.0455
ρ_{nu}	norm	0.000	0.2500	-0.5223	0.0673	-0.6451	-0.3952
$\rho_{n\pi}$	norm	0.000	0.2500	0.0159	0.0855	-0.1244	0.1523
ρ_{gu}	norm	0.000	0.2500	0.0220	0.1255	-0.1626	0.2048
$\rho_{g\pi}$	norm	0.000	0.2500	-0.0612	0.1170	-0.2869	0.1144
$\rho_{u\pi}$	norm	0.000	0.2500	-0.0353	0.0856	-0.1606	0.0925

Table 51: Results from Metropolis Hastings for UK (1985:Q1 – 2013:Q4)

F Graphics of Estimated NAIRU, Unemployment Rate and Inflation Rate (with Survey Data)

The following figures show the estimation of NAIRU. The red curve is the actual unemployment rate, the blue- and black-dotted curves show NAIRU and it's 95% confidence interval respectively, and the grey curve traces the dynamics of inflation.

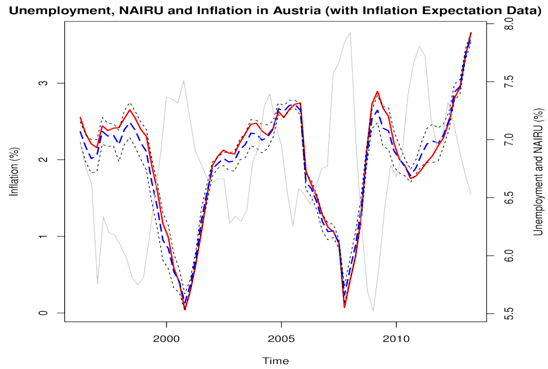

Figure 85: NAIRU for Austria (with survey).

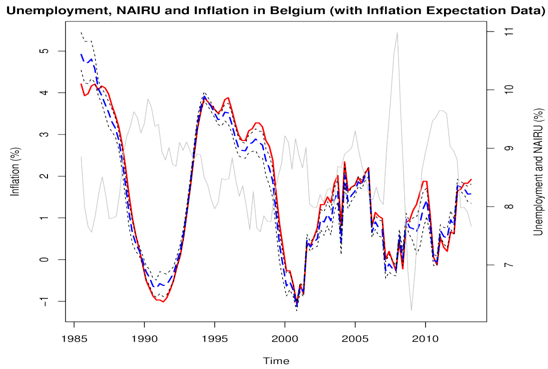

Figure 86: NAIRU for Belgium (with survey).

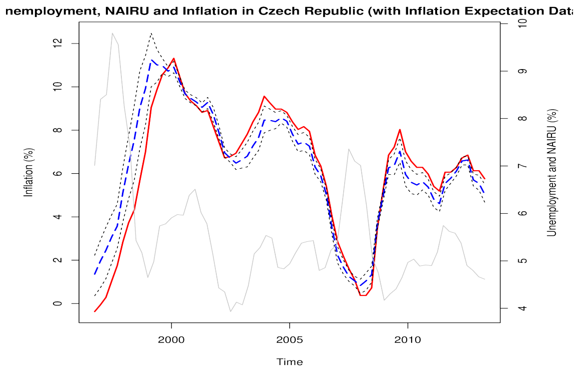

Figure 87: NAIRU for Czech Rep (with survey).

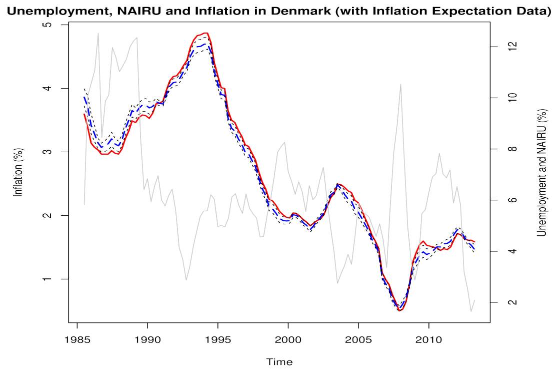

Figure 88: NAIRU for Denmark (with survey).

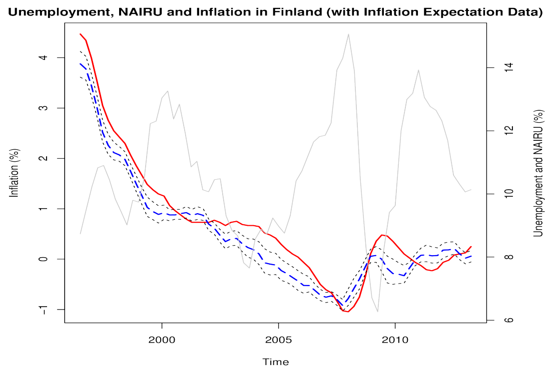

Figure 89: NAIRU for Finland (with survey).

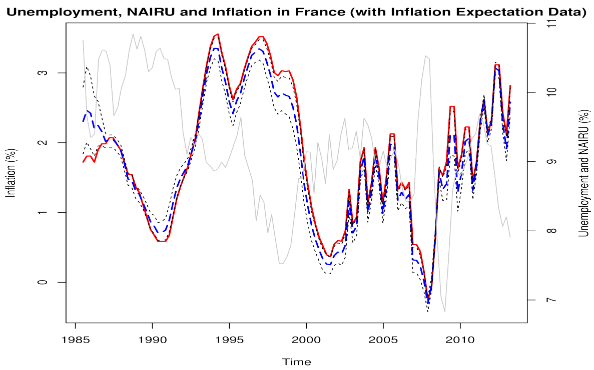

Figure 90: NAIRU for France (with survey).

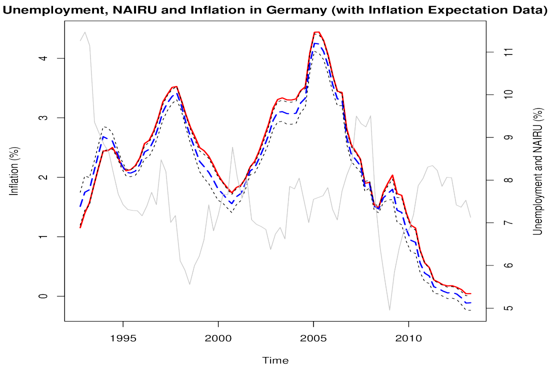

Figure 91: NAIRU for Germany (with survey).

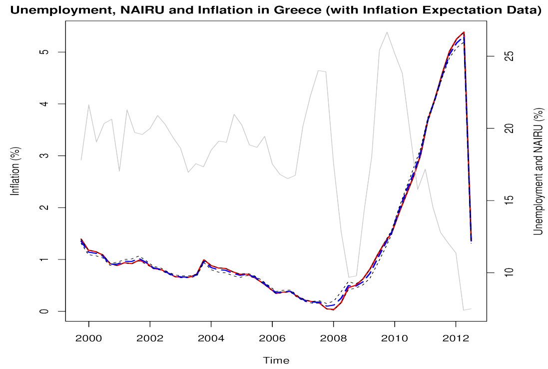

Figure 92: NAIRU for Greece (with survey).

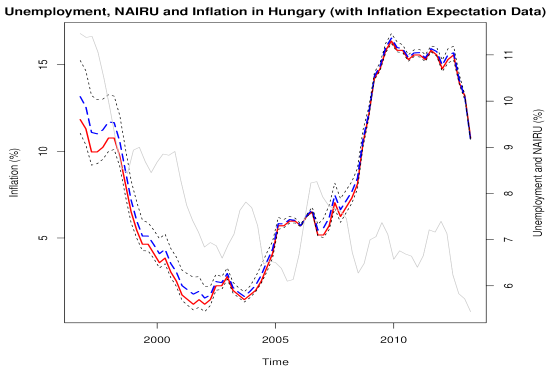

Figure 93: NAIRU for Hungary (with survey).

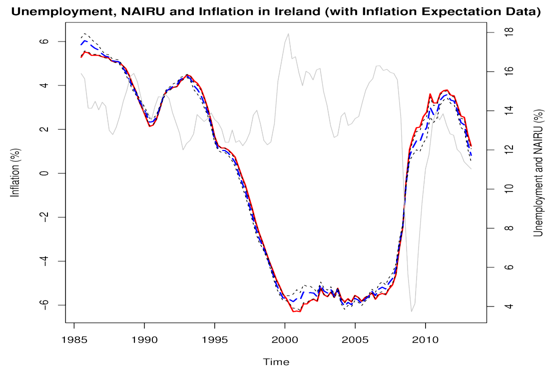

Figure 94: NAIRU for Ireland (with survey).

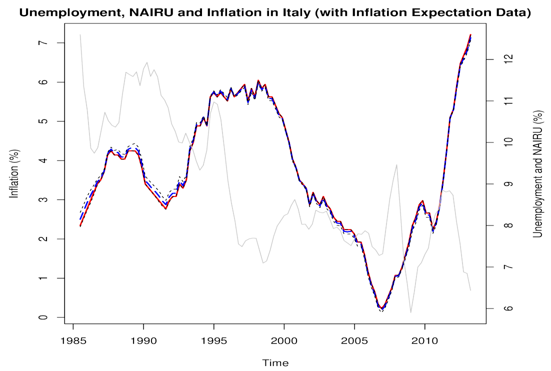

Figure 95: NAIRU for Italy (with survey).

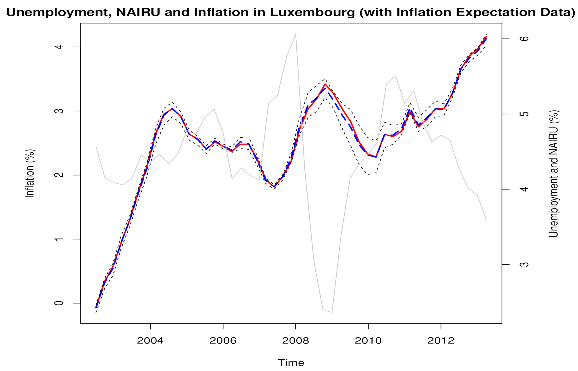

Figure 96: NAIRU for Luxembourg (w.survey).

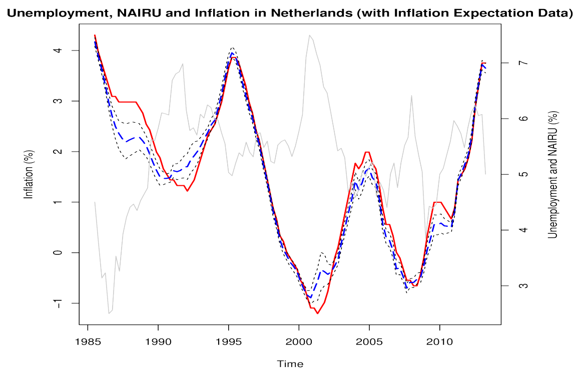

Figure 97: NAIRU for Netherlands (w.survey).

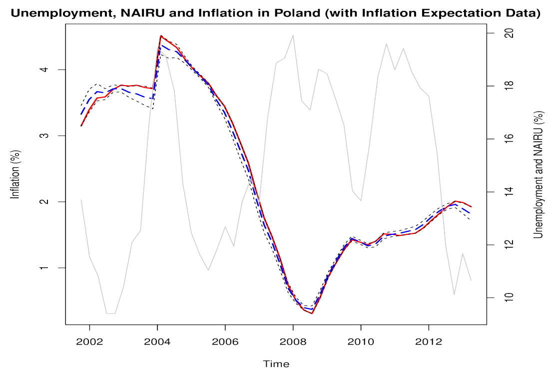

Figure 98: NAIRU for Poland (with survey).

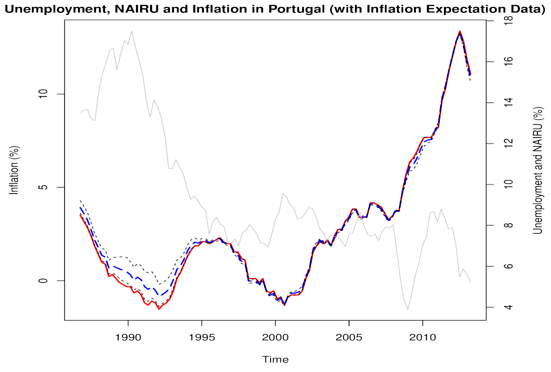

Figure 99: NAIRU for Portugal (with survey).

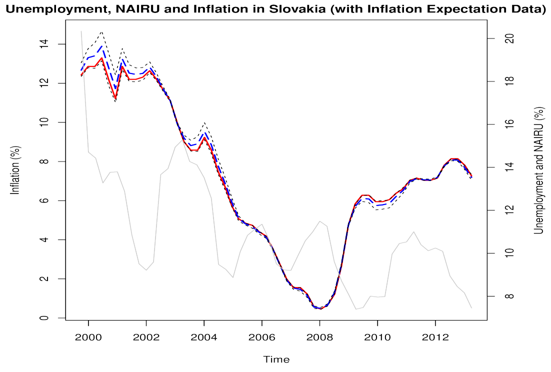

Figure 100: NAIRU for Slovakia (with survey).

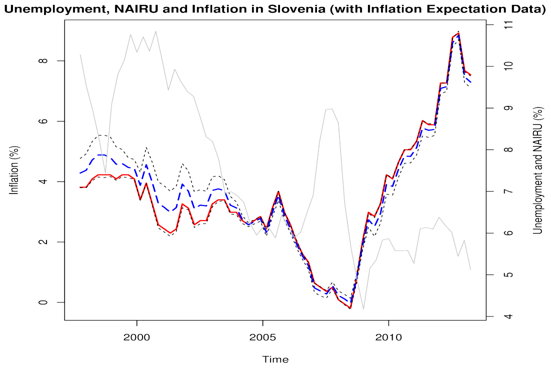

Figure 101: NAIRU for Slovenia (with survey).

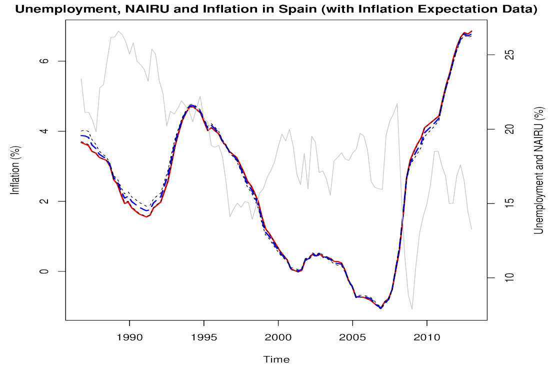

Figure 102: NAIRU for Spain (with survey).

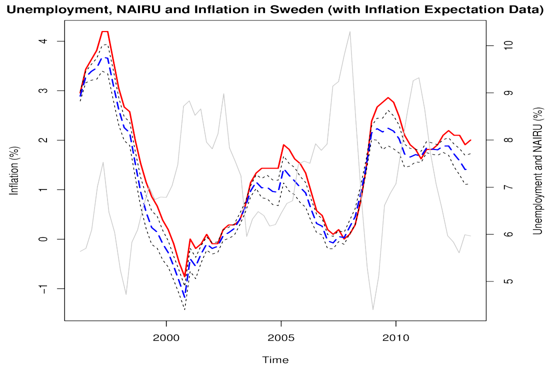

Figure 103: NAIRU for Sweden (with survey).

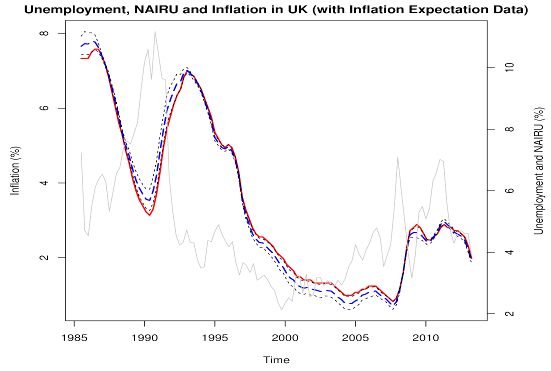

Figure 104: NAIRU for UK (with survey).

G Graphics of Estimated Gaps (with Survey Data)

The following figures show the estimation of output gaps and unemployment gaps, in which two time series of estimated unemployment gap (red curve) and estimated output gap (gery-dotted curve) are drawn together.

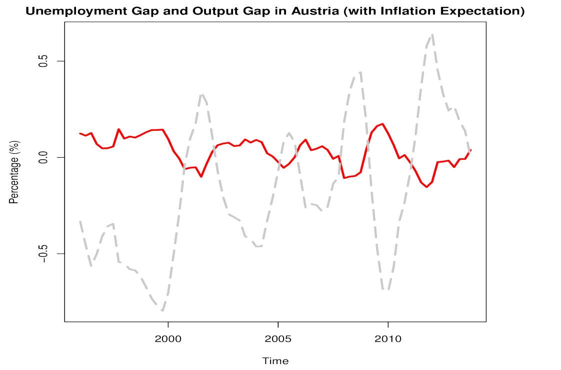

Figure 105: Gaps for Austria (with survey).

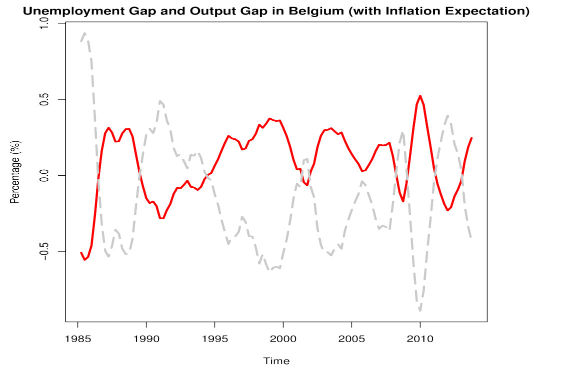

Figure 106: Gaps for Belgium (with survey).

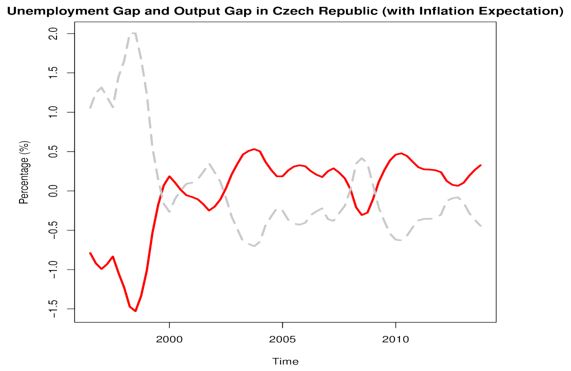

Figure 107: Gaps for Czech Rep (with survey).

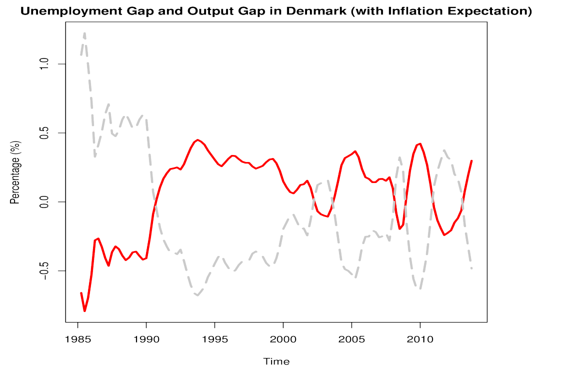

Figure 108: Gaps for Denmark (with survey).

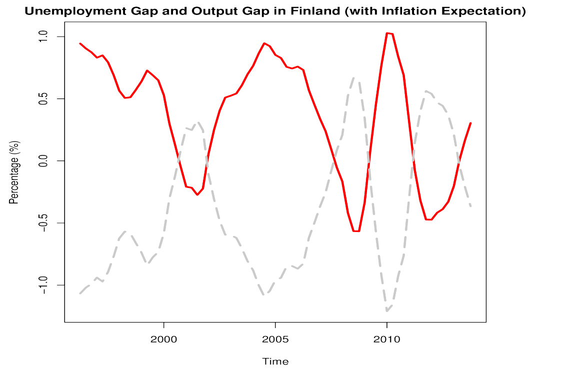

Figure 109: Gaps for Finland (with survey).

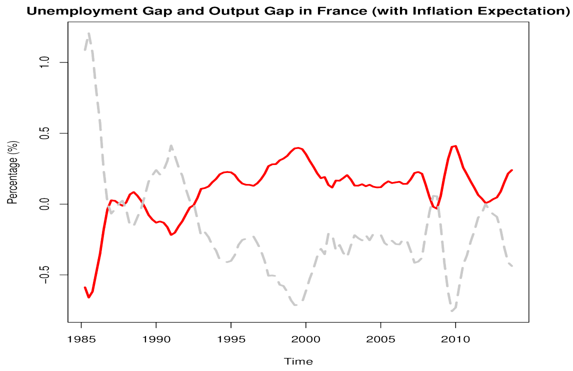

Figure 110: Gaps for France (with survey).

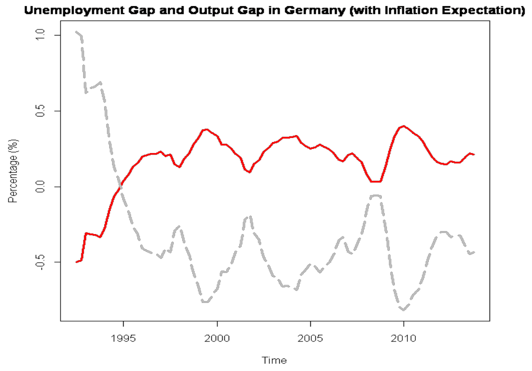

Figure 111: Gaps for Germany (with survey).

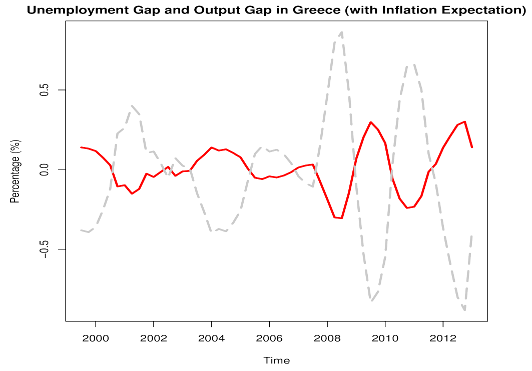

Figure 112: Gaps for Greece (with survey).

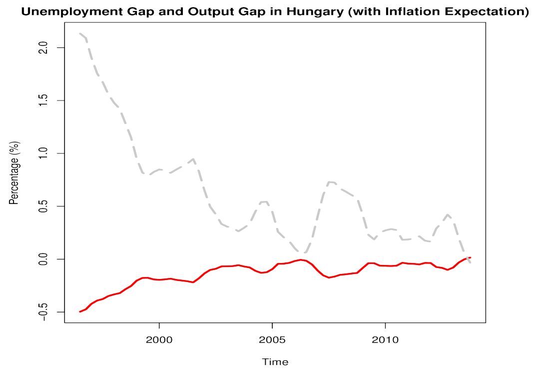

Figure 113: Gaps for Hungary (with survey).

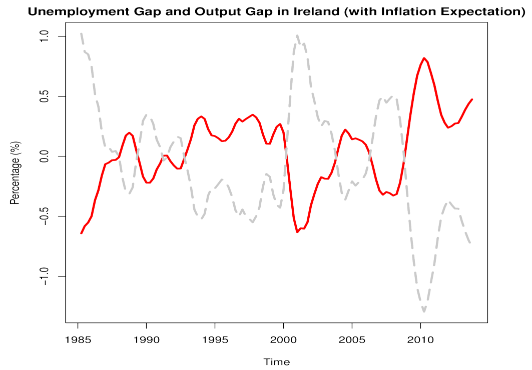

Figure 114: Gaps for Ireland (with survey).

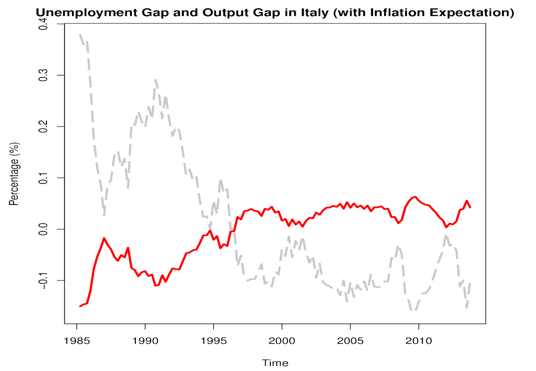

Figure 115: Gaps for Italy (with survey).

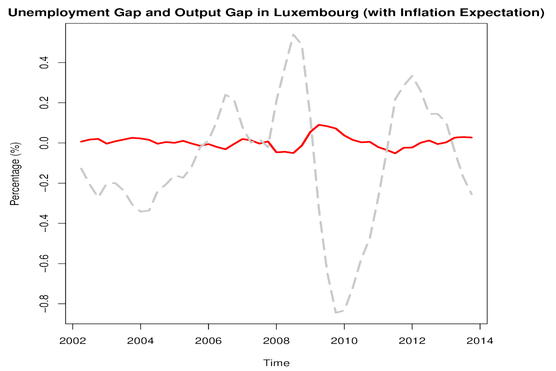

Figure 116: Gaps for Luxembourg (w.survey).

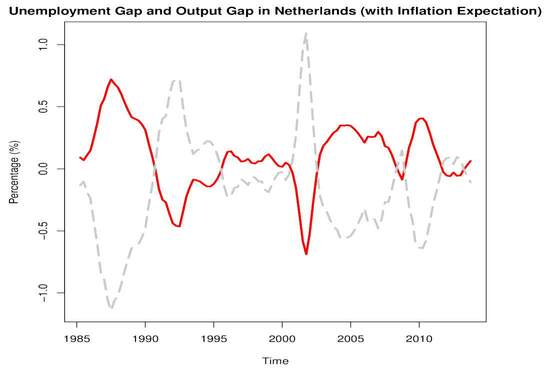

Figure 117: Gaps for Netherlands (w.survey).

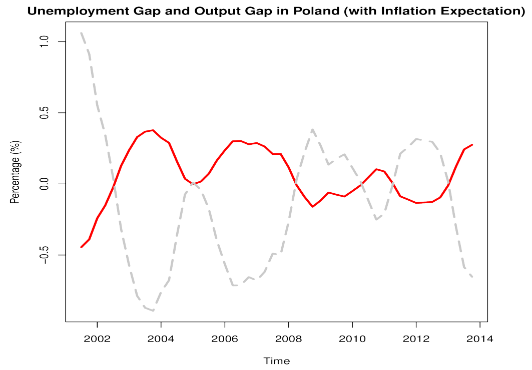

Figure 118: Gaps for Poland (with survey).

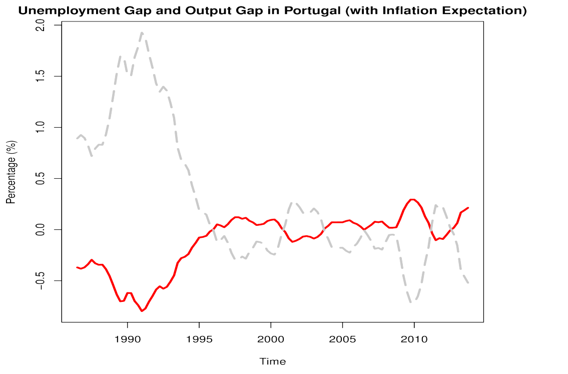

Figure 119: Gaps for Portugal (with survey).

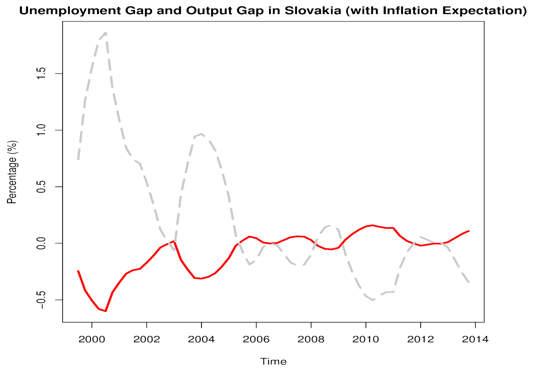

Figure 120: Gaps for Slovakia (with survey).

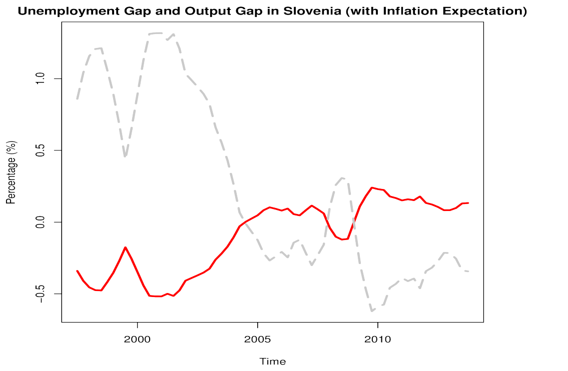

Figure 121: Gaps for Slovenia (with survey).

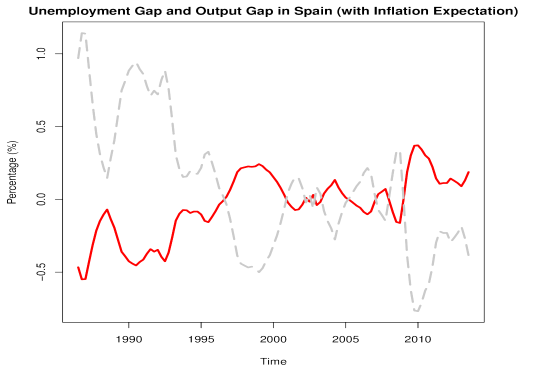

Figure 122: Gaps for Spain (with survey).

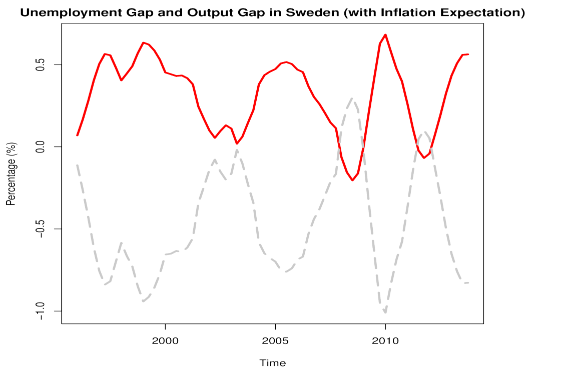

Figure 123: Gaps for Sweden (with survey).

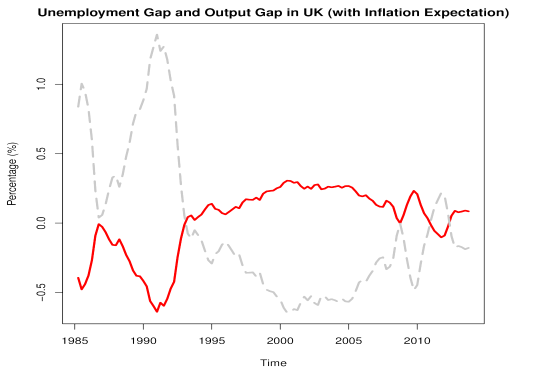

Figure 124: Gaps for UK (with survey).

Declaration of Authorship

I hereby confirm that I have authored this Master's thesis independently and without use of others than the indicated sources. All passages which are literally or in general matter taken out of publications or other sources are marked as such.

Berlin, August 14, 2014

Liang Tong